POLICY EVALUATION, PRODUCTION DECISIONS, AND HAWAI`I'S LONGLINE FISHERY

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ABSTRACT

This dissertation evaluates the policy and production decisions that shape Hawaii's longline fishery. Chapter 1 develops a novel positive mathematical programming framework to evaluate the economic impact to individual fishers from proposed policy changes. Chapter 2 estimates a Bayesian model of the joint production of desirable and undesirable catch and conducts a Bayesian decision analysis to optimize annual sea turtle interaction limits conditional on the value of sea turtles. Chapter 3 examines the labor supply decision of Hawaii's longline fishers by disaggregating the price and quantity components of revenue and estimating their respective relationships to fishers' trip length labor supply decisions.

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1.1 Introduction

Understanding the economic impact of a proposed policy is crucial for ensuring policy objectives are met without being excessively burdensome on the regulated industry. In fisheries, managers are often responsible for preventing over-fishing of common-pool fish stocks. This involves developing policies that balance biological sustainability with economic impacts to the fishing industry. To date, many tools available to managers measure economic impacts at the aggregate industry-level. These tools conceal important information on differences between the impacts felt by individual firms or by types of vessels. Sorting firms that benefit and those that are harmed can help managers understand the economic implications from the policy and which policies are expected to be equitable.

We investigate individual vessel response to fishery policy changes using a vessel and target-specific positive mathematical programming (PMP) model. This research is important for several reasons. To the best of our knowledge, there have only been three previous attempts to apply PMP modeling to fisheries, although none have been published in a peer-reviewed journal.[1][2][3] This provides an opportunity to formalize the PMP model structure for fisheries, which will serve as reference point in the literature and encourage further model development. Given the panel data structure available for Hawaii's longline fishery, we are able to evaluate the performance of the fishery PMP model by comparing out-of-sample predictions to observations from reference years. By calibrating a vessel and target-specific PMP model, this paper provides insights into the range of individual vessel responses to realistic policy changes. Finally, this paper develops a flexible tool for fishery managers to evaluate heterogeneous policy impacts with relatively few data requirements.

Recent research suggests that fisher heterogeneity is particularly important in the Hawaii longline fleet. Fishers have differing attitudes toward risk (Nguyen and Leung 2013), make entry/exit decisions depending on individual fisher characteristics (Pradhan and Leung 2004), and choose remuneration schemes based on owner/operator status (Nguyen and Leung 2009). The network position of individual fishers in the industry has also been shown to play an important role in determining outcomes (Barnes et al. 2015). These studies taken together largely invalidate the common modeling assumption that the Hawaii longline fleet is homogeneous and can be modeled using a representative vessel (Kasaoka 1989 and 1990).

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[1] Niels Vestagaard [1998] Policy Model for a Regulated Industry: From Command and Control to Property Rights in a Danish Multispecies Fishery, Dissertation Chapter.

[2] John Walden [2006] Applying Positive Math Programming to a Fisheries Problem: Formulating the Closed Area Model Structure, Social Sciences Branch, NEFSC, Wood Hole, MA, 02543, Unpublished Manuscript.

[3] Kathereen Bisack and Gisele Magnusson [2009] Modifications to the Harbor Porpoise Take Reduction Plan. Final Environmental Assessment, NOAA-NMFS Northeast Region.

Developing a model of individual vessel response to specific policy changes will, therefore, improve fleet-wide modeling accuracy. For managers of Hawaii's longline fishery, this has added significance given the economic prominence of Hawaii's longline fishing fleet. In 2013, the fleet landed 27,053 tons of fish and generated $88.8 million gross revenues (WPacFIN 2015). The fleet primarily targets swordfish and tuna in the Eastern Pacific and Western and Central Pacific regions. It is the largest commercial fishing fleet by revenue in the state of Hawaii, with between 124 and 135 vessels operating from 2005 to 2013 (WPacFIN 2015).

The geographic scale and environmental effects of the fishery have led managers to implement numerous regulatory policies. The fishery is subject to gear restrictions, turtle bycatch caps, and annual catch limit restrictions. In recent years, the fishery has been forced to close a number of times after these policy limits were reached. In 2006 and 2011, the fishery targeting swordfish was closed because the turtle interaction limit was reached. In 2009, 2010, and 2015, the fishery targeting bigeye tuna in the Western and Central Pacific Ocean was closed because the catch limit had been reached. There is evidence that these closures may have had a dramatic economic impact on both producers and consumers in Hawaii (Allen and Gough 2006).

This paper examines how policies impact individual vessels by calibrating a vessel and target-specific PMP model for Hawaii's longline fishing fleet. By calibrating at the vessel-specific level, we hope to capture the fleet's heterogeneous composition of vessels and heterogeneous response to policy changes. We also account for two primary fishing technologies targeting bigeye tuna and swordfish, and two policy relevant management areas for bigeye tuna, one in the Eastern Pacific Ocean (EPO) and the other in the Western Central Pacific Ocean (WCPO). In order to make our model computationally feasible, and economically tractable we make several assumptions. First, we assume that vessels are profit maximizing. We feel this assumption is appropriate when modeling a large commercial fishing fleet. Second, we assume economic, environmental, and biological conditions are stable, and base year observations are representative of the important economic relationships in the fishery. Under these assumptions, we model the fishery using an objective function that maximizes individual vessel profit subject to fleet-wide annual catch constraints. Individual model parameters are then calibrated to reproduce input and output levels from an observed base year (2012). Using the calibrated model and observed catch data from 2009 to 2013, we then examine model accuracy using out-of-sample model predictions. To demonstrate the model's usefulness to fishery managers, we evaluate the impact of changing the catch limit policies for bigeye fishing in the WCPO.

Although the first application of PMP was more than 25 years ago (Kasnakoglu and Bauer 1988), the PMP framework was formalized by Howitt in 1995. The idea was to blend mathematical programming constraints, which proved useful for modeling resource and policy constraints, with "positive" inferences based on observed input allocations and production levels from a particular base year. This approach was notably different from previous "normative" mathematical programming models (Day 1961, McCarl 1982) in that it was able to exactly reproduce observed inputs and outputs without relying on numerous "flexibility" constraints, which are an additional set of constraints added by the researcher to artificially avoid corner solutions. The general PMP framework can be specified using many structural forms of production and cost functions allowing for non-linearity and substitution between inputs, and can be easily calibrated using observations from a single year. It is both consistent with microeconomic theory, and when applied to policy analysis, is able to generate smooth responses to policy adjustments.

These desirable modeling characteristics have made the PMP approach common in agricultural economic modeling. Recent versions of regional agricultural models employing PMP include SWAP in California (Howitt et al. 2012), CAPRI in Europe (Gocht and Britz 2011), and REAP in the US (Johansson et al. 2007). These models are used repeatedly to evaluate regional agricultural response to policy changes. Heckelei et al. (2012) and Merel and Howitt (2014) provided comprehensive reviews of regional agricultural models currently using the PMP framework and recent developments in the PMP literature. There has also been significant work on developing the economic foundations of PMP, emphasizing accurate estimation of supply elasticities to be used as priors (Merel and Bucaram 2010), structurally consistent estimation of shadow values (Heckelei and Wolff 2003), and improved calibration methods (Garnache et al. 2015).

By applying the most recent PMP framework developed by Garnache et al. (2015), this paper builds on extensive literature modeling fleet dynamics of Hawaii's longline fishery using mathematical programming.[4] The first model by E.R.G. Pacific, Inc. (1986), later modified by Kasaoka (1989 and 1990), applied a linear programming (LP) framework to optimally allocate fishing time across fishing regions and target species to maximize fleet-wide profits. The results, however, did not accurately reproduce observed fishing behavior. Miklius and Leung (1990) evaluated the LP model and concluded that this shortcoming resulted from the omission of micro-level decision-making by vessel owners and operators. To address this problem, Pan et al. (2001) developed a two-level two-objective mathematical programming model which incorporated the behavior of fishers as well as fishery managers, including separate objectives of recreational and commercial fisheries. Their approach produced more plausible optimal solutions, but it remained unclear whether the approximated profit maximizing behavior was representative. The model also assumed that vessels within the fleet were homogenous and was, therefore, unable to capture the variation in vessel responses to changes in management. To address fleet heterogeneity in Hawaii's longline fishery, Yu et al. (2013) used an agent-based model. While the agent-based model was able to capture some of the detailed behavior of individual fishers, there remained a fair amount of discrepancy between predicted and observed performances. The agent-based approach to simulation also required significant model updating and refinement as well as specialized users to operate the software.

Our approach using the PMP framework is intended to be used by policy makers and managers, as well as academics. The vessel and target-specific PMP model is able to capture fleet heterogeneity, separate fishing technologies and regional policies, and measure the distributional effects from changes to fishery policy. It requires minimal data to calibrate, and is amenable to a wide range of resource and policy constraints including catch limits, and protected species interaction caps. It is also able to exactly reproduce base year inputs, costs, revenues, and profits for individual vessels without relying on additional constraints. For these reasons we feel it will be able to address previous modeling limitations.

[4] Curtis and Hicks (2000) investigated the impacts of fishery closure due to turtle interaction caps using a random utility model to account for spatial choice behavior of fishers.

This paper makes four important contributions to the literature. First, the paper adapts the PMP framework developed for agriculture to a framework that can be applied to fisheries in general. With only a handful of notable exceptions, research using PMP for fisheries policy analysis has been very limited. Second, by calibrating a vessel and target-specific PMP model, we are able to demonstrate a technique to examine the heterogeneous nature of the fishing fleet and the heterogeneous responses to specific policy changes. Previous literature on Hawaii's longline fishery has made significant progress to address fleet heterogeneity, but this paper provides a method that explicitly models individual vessels and fish targeting decisions, and requires less data and less effort to calibrate and conduct policy simulations than previous frameworks. Third, it provides a rigorous out-of-sample evaluation of the accuracy of PMP model predictions. Although PMP models have been used extensively for policy analysis, model predictions are rarely evaluated. The panel data we have on Hawaii's longline fishery enable us to make out-of-sample predictions for catch and evaluate the model's predictive accuracy. Finally, the calibrated PMP model of Hawaii's longline fishery provides a valuable tool for resource managers and policy analysts to evaluate the heterogeneous economic impacts of specific fishery policies and determine which policies are likely to encounter industry support or opposition.

1.2 Data

To calibrate the PMP model, evaluate its performance, and simulate policy outcomes, we used data from four sources. We obtained data on individual vessel input costs for 2005 from the 2005 cost and earnings survey (Pan 2015a), and for 2012 from the 2012 cost and earnings survey (Pan 2015b). We obtained data on annual vessel catch from 2005-2013 using the dealer data from the State of Hawaii (Western Pacific Fisheries Information Network 2015). We obtained data on annual hooks deployed from 2005-2013 from Federal logbook data (Fisheries Monitoring and Analysis Program 2015). To evaluate out-of-sample prediction accuracy we adjusted all input and output prices to 2012 dollars using the Consumer Price Index for all urban consumers nationally. Input levels for the variable costs were then scaled relative to the number of fishing hooks deployed to enable efficient optimization during model calibration and simulations. Prices of inputs were adjusted using the inverse scaling ratio to preserve the observed expenditure for each input. We were able to match vessels across data sources using vessel name, permit number, and commercial license.

In 2012, there were 129 vessels operating in Hawaii's longline fishery. Of the 129 vessels operating, 114 were represented in the cost and earnings survey (Pan 2015b). We imputed input cost for missing vessels using random regression imputation considering gear usage, vessel catch profile, and time spent on each target as regression variables. Variable costs were then grouped into six categories: fuel, captain pay, crew pay, bait, other, and gear. We grouped fuel and oil costs under fuel, fixed captain pay and shares paid to the captain under captain pay, combined crew fixed pay and crew shares paid under crew pay, total bait costs under bait, and gear replacement cost under gear. Table 1 shows the degree of fleet heterogeneity based on these inputs. According to the survey data, total variable costs exceeded total gross revenue for six vessels. Rather than dropping these vessels because they violated the profit maximizing assumption, we scaled their input costs such that annual profits were 0.

We then disaggregated individual vessel expenditure, catch, and revenue by three policy relevant targets: bigeye EPO, bigeye WCPO, and swordfish. The EPO and WCPO management regions are separated at 150 W longitude. Bigeye and swordfish fishing sets differ by depth, with swordfish lines set shallower than deep set bigeye lines. We used set-type and location from 2012 logbook data to calculate the proportion of total trip time spent each trip on each target. Trip target time was then aggregated by vessel over the entire year indicating how much time each vessel spent on each target for 2012. Using the dealer data from 2005-2013, we matched vessel trips to observed landings to calculate annual catch and revenue by vessel and target. Observations in the dealer data recorded daily sales. Fish sales were either recorded by individual fish or groups of fish sold together. Daily vessel revenue was calculated by multiplying pounds sold per fish, or group of fish by recorded ex vessel price per pound. The data were then aggregated on vessel and year to calculate the annual pounds of swordfish and bigeye caught, and the total value of vessel catch. These data were then used to calculate fleet-wide average price of swordfish and bigeye, vessel-specific price premium for swordfish and bigeye, and price of non-target catch representing its added value. Input expenditures for each vessel were disaggregated by target according to the proportion of time spent on each target in 2012. Table 2 summarizes the total active fleet size, and model sample size for each target over the years 2005-2013.

1.3 Model Specification

The PMP framework consists of an objective function defining profit maximization and resource and policy constraints that restrict input allocation decisions. To allow for non-linearity in production and limited substitution between inputs we chose to use a generalized constant elasticity of substitution (CES) production function, and for simplicity a linear expenditure function. When paired with a CES production function, the linear expenditure function allows for smooth responses to changes in policy and resource constraints without adding more parameters to calibrate. We define subscript i to index the set of 128 vessels in our sample, r indexes targets EPO, WCPO, and SF, and j indexes inputs for fuel, captain pay, crew pay, bait, other and gear. Given a CES specification the production function for vessel i targeting r is given below.

$$y_{i,r} = \alpha_{i,r}\left(\sum_{j} \beta_{i,j,r}\left(x_{i,j,r}\right)^{\rho}\right)^{\frac{\delta}{\rho}}$$

We define the scale parameter for vessel technology as $\alpha_{i,r}$, input share as $\beta_{i,j,r}$, elasticity of substitution as ρ, and the returns to scale coefficient as δ. By relating effort to catch, the scale parameter is analogous to a vessel-specific catchability parameter in traditional fishery production models. The returns to scale coefficient is defined using a myopic definition (Garnache et al. 2015) relating returns to scale to supply elasticity (η)

$$\delta_{myo} = \frac{\eta}{1+\eta}.$$

Because there have been no direct estimates of supply elasticity of catch in Hawaii's longline fleet, we assume η=0.5, which lies in the range of published supply elasticity estimates for the Gulf of Mexico fishery (Zhang and Smith 2011). To simplify notation, we use a transformed elasticity of substitution defined as

$$\rho = \frac{\sigma - 1}{\sigma},$$

where the untransformed elasticity of substitution (σ) is assumed to be 0.17 for all inputs. At present, we are unable to estimate an elasticity of substitution from the data available, and the value of 0.17 allows for limited substitution between inputs, which we borrow from the agriculture literature and feel is reasonable in a fishery setting (Howitt et al. 2012). Model sensitivity analyses for these assumptions are provided in Figure A1 and indicate our results are robust to changes in assumed parameter values.

Although our production function only models targeted catch, fisher's revenue will depend on their ability to land quality fish, and on the value of non-target but commercially valuable bycatch. To fully capture these components of revenue we model the price of swordfish and bigeye separately for each vessel. The fleet-wide average prices for swordfish and bigeye are given by $p_{i,sf}$, and $p_{i,be}$, vessel-specific price premiums for swordfish and bigeye accounting for variation in quality are given by $p_{i,sfpr}$, and $p_{i,bepr}$, and the additional values from non-targeted bycatch are given by $p_{i,nsf}$, and $p_{i,nbe}$. By adding these three components together, we specify a vessel-specific price for bigeye (BE), and swordfish (SF).

$$p_{i,SF} = p_{i,sf} + p_{i,sfpr} + p_{i,nsf}$$

$$p_{i,EPO} = p_{i,WCPO} = p_{i,be} + p_{i,bepr} + p_{i,nbe}$$

This specification allows us to exactly reproduce observed vessel revenue, while only modeling the production of the policy relevant targets. Implicit in this price specification we assume the price of bigeye from the EPO is the same as bigeye from the WCPO, which we feel is reasonable given they belong to the same species and are both caught throughout the year.

For simplicity, we specify a linear expenditure function. The input cost data only provides total annual costs per input, therefore we assume input prices ($c_{i,j,r}$) are 1, which implies input levels ($x_{i,j,r}$) are in dollar units. The choice set $x_{i,j,r}$ is the vector of individual vessel input levels for each target. Profit maximization is constrained by three policies. We model annual catch limits for bigeye tuna in the EPO (ACL_{EPO}) and WCPO (ACL_{WCPO}), and a total annual catch limit for swordfish (ACL_{SF}). Vessel heterogeneity implies that the unobserved value of catch for each constraint will vary by vessel. We therefore define the unobserved value of catch as $\mu_{i,r}$ over vessels and targets. The maximization problem is given below.

$$\max_{x_{i,j,r}} \sum_i \sum_r \left[(p_{i,r} + \mu_{i,r}) y_{i,r} - \sum_j c_{i,j,r} x_{i,j,r} \right]$$

$$s.t.$$

$$\sum_i y_{i,EPO} \le ACL_{EPO}$$

$$\sum_i y_{i,WCPO} \le ACL_{WCPO}$$

$$\sum_i y_{i,SF} \le ACL_{SF}$$

1.4 Model Calibration

We adapted the calibration procedure developed by Garnache et al. (2015). Their calibration procedure is the most recent methodological advance in the PMP literature, comprehensively addressing the criticism by Heckelei and Wolff (2003) regarding the calibration of shadow values. Rather than estimated using an LP or ad hoc measures as was done previously, all unknown parameters and the shadow values are calibrated simultaneously using the same structural forms as used in model simulations, in this case a CES production function with a linear expenditure function. Garnache et al. (2015) calibrated a PMP model for agriculture. In agriculture, the constrained input is typically land, however, in fisheries, production inputs can be purchased at any desired level on a common market and the constrained resource is catch. We adapted the calibration procedure to account for this difference. For each target we specified a shadow value (λ_r). We then calibrated the model by minimizing the sum of squared error between observed expenditures and model expenditures resulting from the choice variable λ_r as specified below.

$$\min_{\lambda} \sum_{i} \sum_{r} \left[(p_{i,r} + \lambda_r)\bar{q}_{i,r}\delta - \sum_{j} c_{i,j,r} \right]^2$$

The objective function is subject to four sets of constraints that determine the calibration of unknown parameters. The first set of constraints requires production parameters reproduce observed output ($\bar{q}_{i,r}$) for each vessel and target.

$$\bar{q}_{i,r} = \alpha_{i,r} \left(\sum_{j} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho} \right)^{\frac{\delta}{\rho}}, \forall\, i, r$$

The second set of constraints requires the first order conditions of profit maximization hold. The first order condition will be specified for each input, vessel, and target as below.

$$p_{i,r}\alpha_{i,r}\delta \left(\sum_{j} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho} \right)^{\frac{\delta}{\rho}-1} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho-1}$$
$$= c_{i,j,r} - (\lambda_r + \mu_{i,r})\alpha_{i,r}\delta \left(\sum_{j} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho} \right)^{\frac{\delta}{\rho}-1} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho-1}, \forall\, i, j, r$$

The third set of constraints allows us to recover the vessel and target-specific unobserved value of catch ($\mu_{i,r}$).

$$p_{i,r} \sum_{j} \left[\alpha_{i,r}\delta \left(\sum_{j} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho} \right)^{\frac{\delta}{\rho}-1} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho-1} \right]$$
$$= \sum_{j} c_{i,j,r} - (\lambda_r + \mu_{i,r})\alpha_{i,r}\delta \sum_{j} \left[\left(\sum_{j} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho} \right)^{\frac{\delta}{\rho}-1} \beta_{i,j,r} \left(x_{i,j,r} \right)^{\rho-1} \right], \forall\, i, r$$

Finally, our calibration procedure requires that for each vessel-target combination the sum of the input share parameters is one.

$$\sum_j \beta_{i,j,r} = 1 \,, \forall\, i, r$$

1.5 Calibration Results

The PMP model calibration procedure is designed to calibrate unknown parameters and constraint shadow values such that profit maximizing vessels, subject to the base year resource constraints, will optimally allocate the observed base year levels of input, generating the observed outputs and revenues, and the observed expenditures. To evaluate whether the calibration was successful, we examine the range of calibrated parameter values and the differences between the observed and the modeled input levels using the base year catch constraints in 2012.

In Table 3, we present the range of calibrated model parameters. The largest magnitude of variation is found in unobserved shadow prices of catch and the scale parameters. These parameters carry the most weight for modeling the heterogeneous responses of the fleet. The share parameters also show significant variation indicating the model captured a large amount of vessel heterogeneity in input expenditures. Across targets, the share parameter for fuel are consistently larger than the other inputs, which is expected given fuel is the largest single input cost. To verify the calibration procedure, we examine the differences between observed and modeled input levels for each input and each vessel's output using the base year constraints. The largest difference in input is $2.02\text{x}10^{-14}$% and the largest difference in output is $9.53\text{x}10^{-6}$%. Such small differences indicate that we achieve an accurate calibration of all unknown parameters, and that our model can very closely replicate the observed base year economic behavior of each vessel.

To further verify the calibration procedure, we compare the shadow values to the observed average price per pound of fish. The shadow value on each resource constraint can be interpreted as the value of relaxing the resource constraint by one pound of either bigeye or swordfish. Taken in absolute value terms, the calibrated shadow values of -7.70, -7.57, and -4.45, representing bigeye catch in the WCPO, EPO, and swordfish catch respectively, appear to be accurately calibrated. When compared to the average observed price per pound of bigeye, and swordfish ($7.99, $4.30 respectively), our calibrated shadow values are within a few cents of the average observed fish prices. Although average prices and shadow values do not share the same interpretation, comparing the two does provide a useful validation of the overall calibration procedure.

1.6 Prediction Accuracy

We evaluate model predictions in two ways. First, we compare predicted and observed catch from 2009 to 2013. Of the 128 vessels modeled, 126 were operating in 2013; however, going back to 2009, as few as 119 of the original 128 were previously operating (Table 2). For each year, we simulate the model by setting the fleet-wide catch constraint less than or equal to the total observed catch of the vessels remaining from our 2012 sample. This implies that our simulated fleet size decreases as vessels operating in 2012 are no longer observed in more distant years. To account for changes in input costs over time, we adjust the cost of fuel using U.S. number 2 diesel retail price[5] and the costs for captain pay and crew pay using annual salary data from Bureau of Labor Statistics occupational profiles for farming, fishing, and forestry occupations.[6] Regressing the predicted revenue on observed revenue for the years 2009-2013, we examine the correlation coefficient and the amount of variation explained by our model (Figure 1). We find the model performs best predicting bigeye catch in the WCPO, modestly for bigeye catch in the EPO, and poorly for swordfish catch. The best out-of-sample model predictions are made for the 2011 bigeye catch in the WCPO (R-squared=0.35, correlation coefficient=0.53). For all targets, model predictions become less accurate moving further in time away from the calibrated base year. This is expected as biological stock level, individual fishing location decisions, and environmental conditions could vary substantially over this time, while our model assumes conditions remain constant. In the short-term the model makes reliable predictions of individual vessel catch for the largest target in the fishery, bigeye in the WCPO.

Second, we evaluate the model input level predictions for each target comparing the observed input levels from the 2005 cost and earnings data to the predicted input levels simulated using our PMP model. Results are shown in Table 4. In order to compare the values, we match vessels that appear in both sets, reducing our sample to 71, 25, and 1 for the WCPO, EPO, and SF targets respectively. Results from a paired Wilcoxon test comparing the observed and predicted input expenditures show the model significantly under-predicts all inputs except gear and bait for the WCPO target. The model tends to over-predict input costs for the EPO target, and it over-predicts all inputs except fuel for the one matched vessel targeting SF. By comparing observed expenditures in 2012 (Table 1) to 2005 (Table 4), the primary source of prediction error is the large differences in the observed expenditures between 2012 and 2005. For instance, fundamental changes to the remuneration schemes over these years, including the wide-spread transition from crew shares paid to domestic crew to fixed pay for foreign crew, could account for the observed differences in crew pay and captain pay. We also observed a reduction in fuel expenditures in 2005 in the WCPO and EPO, and increase in SF, which could reflect a change in fishing grounds requiring more or less travel time than in 2012. Similar explanations could account for differences in other input expenditures predicted for each target. Gear and bait expenses, which we expect to be most closely tied to catch, generate the closest predictions and are not sensitive to changes in remuneration scheme or fishing location. Any changes to the fundamental cost structure of the fleet are expected to alter model parameter values and reduce the accuracy of forecasts. This limitation is common to all model based forecasts.

1.7 Policy Simulations

[5] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMD_EPD2D_PTE_NUS_DPG&f=A
[6] http://www.bls.gov/oes/tables.htm

To demonstrate the usefulness of a vessel-specific PMP model for Hawaii's longline fishery, we examine vessel responses and impacts on individual vessel catch to changes in the annual catch limit policy. We simulate two policy changes. The first is a policy that increases the annual catch limit of bigeye in the WCPO by 10% from the 2012 base year. The second is a policy that decreases the same catch limit by 10% from the 2012 base year. A 10% change in the catch limit policy is roughly in line with the agreed upon changes for bigeye in the WCPO in the next few years which will see catch limit decrease 11% from 3,763 metric tons in 2014, to 3,345 metric tons in 2017.

The vessel-specific nature of our PMP model allows us to evaluate the distributional effects of such policy changes. We expect that individual vessels will respond to varying degrees, depending on factors such as technological efficiency and profitability, which makes them more or less sensitive to policy changes. In Figure 2, we present the distribution of catch responses given an increase and decrease in bigeye catch limits in the WCPO. The range of responses is large. With a 10% increase in catch limit, we see that vessels respond by increasing catch from less than 5% to 20%. With a 10% decrease in catch limit, the responses are symmetric to the 10% increase policy. Vessels reduce catch from less than 5% to 25%. Given the range in policy responses, individual vessels will clearly be affected differently. Some will be highly sensitive to policy changes; most will experience moderate impacts. Understanding the distributional implications is clearly important for evaluating economic impacts of fishery policies in Hawaii's longline fishery.

1.8 Conclusions

In this paper, we have shown that the vessel and target specific PMP model of Hawaii's longline fishery reliably predicts short-term effect of policies on bigeye catch in the WCPO and EPO. Model predictions are more accurate when simulating vessel responses close to the base year, but lend some insight even at further distances. By calibrating at the vessel-specific level, we are able to identify the range of economic responses to policy changes, capturing the heterogeneous nature of Hawaii's longline fleet. This more realistically models vessel responses, as well as provides an evaluation of the distributional effects of policy changes on catch, which is important for evaluating the stability of new policies. For fishery managers, the PMP model of Hawaii's longline fishery provides a valuable tool for evaluating the economic impacts of current and potential fishery policies.

The PMP framework also provides a rich structural model with which we can study fisheries in general. Later work will address parameter instability resulting from fundamental changes to underlying economic relationships or environmental and biological conditions, and estimate target switching decisions made by fishers. We will also consider the effects of overlapping policy constraints such as turtle interaction caps, and explore the individual vessel characteristics that make certain vessels more sensitive to policy changes than others.

2. BALANCING GOODS AND BADS: A BAYESIAN ANALYSIS OF FISHERY REGULATORY DECISIONS

2.1 Introduction

Many industries jointly produce desirable and undesirable outputs. When production of undesirable outputs causes noticeable damage, such as harming fish in a stream in Stigler's (1952) example, demand for regulation grows. But, industry regulators face a trade-off. If they set regulations too loosely, the industry continues to generate an excess of undesirable outputs. Conversely, if their regulations are too tight, the industry produces fewer desirable outputs.

Coase (1960) provided a generalized model for such a decision problem. He framed the problem with respect to two firms: A and B. He noted that if the activity of A harms B, any restraint of A would also cause it harm. The regulatory decision then becomes whether, and to what extent, A should be allowed to harm B, or B to harm A. It becomes clear from Coase's model that the initial reason for a given regulatory decision, that is to keep A from harming B, provides insufficient support for regulatory restraint. Regulators must also account for the damages caused to the other firm by their regulatory decision. Coase determined that the appropriate decision only becomes clear once we know the value of the damages, and the value that is lost to reduce those damages. In practice, these values are rarely made transparent during the decision process. Yet, without this information, we are unable to evaluate regulatory decisions, and judge whether or not they are optimal. To solve this problem, we need a transparent methodology to estimate these values, and clearly show how they affect regulatory decisions.

In this paper, I present an analysis of the regulatory decision problem facing fishery managers tasked with balancing desirable fish catch with undesirable bycatch. In particular, I focus on bycatch regulations pertaining to endangered sea turtles caught by Hawaii's longline fishery. Fishery managers are directed by legislation to promote commercial fishing "under sound conservation and management principles (Magnuson-Stevens Act 104-297)." As applied to Hawaii's longline fishery this directive presents managers with a decision problem: How much should they restrain commercial fishing in order to protect endangered sea turtle populations? I evaluate the fishery manager's decision using a Bayesian model of production, and Bayesian decision analysis.

My approach proceeds in two steps. First, I estimate a model of production, accounting for the joint production of desirable and undesirable outputs. Then, using the estimated model parameters, I solve the social utility maximization problem facing decision-makers. However, the solution relies on knowing the social value of sea turtle bycatch, which is not well known. I therefore iterate over a wide range of possible social values and calculate the optimal regulation that maximizes the expected utility for each iteration. This step, effectively reverse engineers the decision analysis. Rather than choosing a decision to maximize expected utility given known social values, I calculate the optimal decision for every social value in a reasonable range. This iterative process results in a guide that maps the social value of sea turtles to optimal sea turtle regulations. I thereby uncover the implicit values regulators used to set observed regulations, assuming they were maximizing utility.

This approach is based on statistical decision theory outlined by Berger (1985) and more recent work by Lin et al. (1999) and Gelman et al. (2013). The general framework uses statistical inference to predict the quantities that enter into a specific decision problem. For Hawaii's regulatory decision problem, these quantities include the value of sea turtle protection and the value of restraining fishery production. The approach is statistical in that the quantities may not be precisely measured, or the decision process may involve inherent uncertainty. To solve the decision problem under uncertainty, a researcher numerically maximizes the expected utility over the set of possible decisions. The utility function is assumed and represents the value of gains and losses resulting from a particular decision. Although the decision is sensitive to the accuracy of the model and how utility is specified, decision analysis succeeds in making the values that enter the decision process transparent. With regard to Coase's regulatory framework, decision analysis provides a tool to solve decision problems where the optimal decision balances a tradeoff between damages from production, and damages to production from regulatory restraint.

In order to fit the decision theory framework to evaluate sea turtle regulations I make several modifications. I first address missing information on the value of sea turtles. Sea turtles are a non-market good, therefore estimating the value of their protection is challenging. To resolve this limitation, I modify the decision optimization problem. I assume decision makers maximize utility when setting regulations, then iterate over a reasonable set of sea turtle values an solve for the level of regulatory protection that maximizes utility. This process reverses traditional decision analysis, but similarly succeeds in making quantities transparent.

The second modification addresses the infrequent rate of sea turtle bycatch events. Interacting with sea turtles is rare in Hawaii's longline fishery, therefore a model of these events must account for over-dispersion. One way to minimize bias when modeling rare events is to aggregate observations, in this case to the industry-level (Dixon et al. 2005, Kvamsdal et al. 2013, and Martin et al. 2015). I therefore specify a multilevel model of production with desirable fish catch predicted at the firm-level and undesirable sea turtle bycatch predicted at the industry-level. These modifications allow me to evaluate the regulatory decision facing Hawaii's fishery managers. They also expand the range of decision problems for which decision analysis is useful. The fishery problem shares many characteristics with other important industries, such as nuclear power generation, and offshore oil drilling. In each of these industries, regulators must decide how much production to promote, when production carries the risk of severe environmental damage. The modified decision analysis I develop can be extended to evaluate these decisions as well.

I fit the model to unbalanced panel data from Hawaii's longline fishery collected for 204 vessels operating between 2004 and 2013. These data consist of annual input and output levels for three categories of desirable fish catch observed at the firm-level. Annual sea turtle interactions for two endangered species, loggerhead and leatherback sea turtles, are observed at the industry-level. Estimates of production parameters, including technical and environmental efficiency, come from fitting a set of models using Bayesian inference. I then conduct posterior predictive checks to verify that estimates match empirical observations.

Results from these checks provide confidence in the model estimates. Numerical samples are then drawn from posterior densities to solve the decision analysis problem.

I develop a set of statistical models and a decision analysis to evaluate the regulatory decision fishery managers must make to balance the commercial production of Hawaii's longline fishery with endangered sea turtle protection. Section 2 provides background on the fishery, describing the production process and pointing to key literature on the fishery which helps inform model parameterization. Section 3 describes the data I use to estimate the model, and modifications I make to the raw data. In Section 4, I develop a multioutput stochastic frontier model to capture the joint production of desirable outputs, a Poisson model of the production of undesirable outputs, and summarize the estimation results, and posterior predictive checks I use to evaluate model fit. Section 5 presents the full Bayesian decision analysis and results. I conclude in Section 6 with a discussion of the model's implications for the actual decision process, limitations of the current approach, and the relevance to other regulatory decision problems.

2.2 Fishery Background

Hawaii's longline fishery provides an ideal context to examine regulatory decision making. The fishery produces multiple species of desirable commercial catch, as well as undesirable bycatch. The wide range of outputs is a result of the production technology employed by fishers. Fishers harvest fish using longline gear, consisting of a mainline up to 100 km long, suspended by floats, with baited hooks descending at regular intervals (Boggs et al. 1993). Together this fishing gear forms a set. Fishers choose whether to target tuna or swordfish by placing the set deep in the water column to target tuna, or shallow to target swordfish. Although tuna and swordfish are the primary target species, the fishing gear is not perfectly selective. A total of 21 commercially managed species are caught using this gear. The gear also interacts with undesirable species. Endangered loggerhead and leatherback sea turtles are of primary concern, but sea birds and protected marine mammals are also at risk of being caught.

Joint production of desirable, and undesirable outputs prompted regulators to intervene. In 1999, the Western and Central Pacific Fishery Commission implemented an emergency closure of the entire fishery in response to concern over the level of sea turtle bycatch. This was followed by a prolonged closure of the swordfish sector, which has the highest risk of sea turtle interactions, from 2002 through the end of 2003. In 2004, the swordfish sector was reopened with new gear restrictions, mandated federal observers, and annual sea turtle interaction limits set to 17 loggerhead and 16 leatherback sea turtles. As a result of these limits, the swordfish sector closed early in 2006, and again in 2011. Sea turtle limits were then relaxed in 2012 to allow 34 loggerhead and 26 leatherback interactions, and has remained open.

The fishery has been the subject of extensive research, and as a result has a well-documented history (Pooley 1993) creating a rich literature from which to build. The most relevant information includes results from a previous evaluation of Hawaii's production efficiency, and a series of papers estimating the value or cost of sea turtle bycatch. The production efficiency of Hawaii's longline fleet was estimated by Sharma et al. (1998). They evaluated each fisher's efficiency relative to an estimated ideal production technology, and found the average efficiency of the fleet is 84%. This will serve as a prior for estimating the model developed in the Section 4.

Following the initial closure of the swordfish sector, a series of papers estimated the impact of sea turtle bycatch regulations using a variety of modeling approaches. The first assessment of Hawaii's sea turtle regulations was published shortly after the first temporary closure in 1999 by Curtis et al. (2000). The authors use a random utility model, and estimate the cost of reducing sea turtle bycatch to be $52,976 per turtle, or $41,262 per turtle if tuna fishing is exempted from the regulatory closure. Several subsequent papers use a mathematical programming approach to estimate the shadow value of sea turtle bycatch. Pradhan et al. (2006) estimate the shadow value in terms of lost revenue as $56,060, and in a later paper incorporating spatial and seasonal dimensions, they estimate a larger shadow value of $60,908 (Pradhan et al. 2008). Finally, Huang et al. (2007) use a directional distance function approach to estimate the shadow price of sea turtle bycatch to be $30,873. Results from this literature will serve as a comparison to the results generated using a Bayesian decision analysis. Comparing these two types of estimate for sea turtle values reveals a clear difference in methodology. Values obtained from Bayesian decision analysis measure the implicit social value of a sea turtle conditional on the level of sea turtle protection, whereas the shadow price of sea turtles reflects the change in revenue or profit from relaxing the sea turtle constraint by 1 turtle.

2.3 Data

I draw on three data sources to develop two panels of fishery observations from 2004 to 2013. Federal observer data counts the number of sea turtle bycatch events. Logbook data records the start and end date for each fishing trip, and the time and date for each set deployed during the trip. Dealer data records the pounds sold and the price per pound for each commercial species landed at the Honolulu fish auction at the end of each trip. Nearly all landings from Hawaii's longline fleet are sold at the Honolulu fish auction. The sample period is restricted by data availability. Federal observers began data collection in 2004 as part of the regulations reopening swordfish fishing, and my access to logbook and dealer data only includes observations through 2013. This sample period, however, includes the first 10 years under which the fishery was regulated by annual sea turtle bycatch limits.

The two panels summarize data at two levels: firm-level and industry-level. The firm-level panel measures annual fisher activity through a set of inputs and outputs, where the unit of observation is fisher i in year t. To generate the firm-level panel I first combine logbook and dealer data, matching on vessel name and landing date. This results in a set observations from each trip taken by each vessel over the sample period. Using the logbook data, I define a new variable for set type, which takes the value of either deep set, or shallow set based on the time the set was deployed. Regulations require that shallow sets be deployed at night. I then calculate trip duration from the recorded departure date and return date, and define this as a new variable. Using the dealer data, I aggregate fish catch into three categories: bigeye tuna, swordfish, and other. For each category, I sum the total pounds landed each trip, and record the average price per pound. Because fishers take several trips in a year, I sum fishing duration, number of each set type, and catch for each vessel each year creating a panel of annual inputs and outputs for 204 vessels operating from 2004 to 2013.

The industry-level panel summarizes the number of sea turtle bycatch events observed each year. Although I treat these observations as industry-wide, they are in fact limited to observations from Federal observers aboard vessels targeting swordfish. Trips that target tuna are not subject to 100% observer coverage. Because of the overlap between shallow set gear and sea turtle habitat, swordfish trips are much more likely to interact with sea turtles, therefore, the assumption that these observations measure sea turtle bycatch across the entire industry is reasonable. For the sample period 2004-2013, I use publicly available annual sea turtle bycatch counts for loggerhead and leatherback sea turtles. In 2006 and 2011, these counts reflect binding sea turtle regulations forcing the shallow set sector to close prematurely.

2.4 Models

The goal of the following models is to represent the production decisions of fishers in Hawaii's longline fishery and estimate the production processes by which outputs are generated. This includes estimating both the productivity of the fishing technology, and the technical and environmental efficiency when fishers use this technology to produce desirable and undesirable outputs. In this section, I introduce the stochastic frontier framework, and develop a set of models for the production of multiple desirable and undesirable outputs in Hawaii's longline fishery.

2.4.1 Multioutput Stochastic Frontier Model

Stochastic frontier models were first developed by Aigner et al. (1977) and Meeusen et al. (1977) to estimate the technical efficiency of individual firms using a common production technology. Efficiency was measured as a percentage of the estimated ideal production level conditional on input decisions. The advantage of their approach over alternative mathematical programming methods (DEA), was the inclusion of a stochastic error component. This accounted for measurement error and variation in production technology. Firm-specific efficiency could then be identified by specifying an additional one-sided error term.

To illustrate, imagine a set of I firms. The stochastic error term is defined as ϵ, and assumed to follow a normal distribution. Firm-specific efficiencies are defined μ_i, and given strictly positive distributions, typically a half-normal, exponential, or gamma distribution. Then, given a set of firm i's input decisions, $\boldsymbol{x_i}$, and production function $f(\boldsymbol{x_i})$, firm i's output y_i is modeled by the following:

$$y_i = f(\boldsymbol{x_i}) \exp(-\mu_i) \exp(\epsilon) \tag{1}$$

By log transforming both sides, the model becomes linearized, and model parameters, including firm-specific technical efficiencies, μ_i, can be estimated using least squares, maximum likelihood, or Bayesian estimators (Green 2003).

Stochastic frontier modeling has proved useful for identifying the various components contributing to variation in productivity among firms and across time. In addition to variation in technology and scale of production, the stochastic frontier model estimates firm-specific operating efficiency. The combination of these parameters in a single model creates a meaningful description of firm-specific production in an industry.

In the simplest formulation, the model is limited to production of a single desirable output. More recent literature has extended the framework to production of multiple outputs. Building on the Bayesian estimation procedure, Fernandez et al. (2000) accommodate multiple output technologies using an output transformation function. The function aggregates a P-dimensional output vector, $\boldsymbol{y}_i$, as a univariate parameter θ_i, given by the following function:

$$\theta_i = \left(\sum_{j=1}^{P} \alpha_j^{\sigma} y_{i,j}^{\sigma} \right)^{1/\sigma} \qquad 2$$

where $\alpha_j$provides a scale adjustment for individual outputs, and σ defines the elasticity of transformation between outputs, which determines the curvature of the production equivalence surface. For $\sigma > 1$ the production equivalence is concave, and for $\sigma < 1$ it is convex. The transformation θ_i is then substituted for y_i in the original stochastic frontier model to estimate technical efficiency for firms jointly producing multiple outputs.

I modify the previously developed multioutput stochastic frontier framework to model desirable outputs in Hawaii's longline fleet. Recall the stochastic frontier model defines the level of output, $y_{i,t}$, as a function of inputs, $f(\boldsymbol{x}_{i,t})$, firm efficiencies, μ_i, and stochastic error, ϵ, as given below.

$$y_{i,t} = f(\boldsymbol{x}_{i,t}) \exp(-\mu_i) \exp(\epsilon) \qquad 3$$

After log transforming both sides, I can write the model, assuming a random normal standard deviation σ_θ as

$$\log(\theta_{i,t}) \sim \mathrm{N}\left(\log\left(f(\boldsymbol{x}_{i,t})\right) - \mu_i, {\sigma_\theta}^2\right). \qquad 4$$

For fisher i operating in year t, the fisher chooses a K-dimensional vector of inputs, denoted $\boldsymbol{x}_{i,t}$, which are then transformed into a P-dimensional vector of desirable commercial catch, $\boldsymbol{y}_{i,t}$. I aggregate the vector of desirable outputs using the following specification of $\theta_{i,t}$:

$$\theta_{i,t} = \left(\sum_{j=1}^{P} y_{i,t,j} \right). \qquad 5$$

I drop the scale adjustment term from Fernandez et al. (2000) because all outputs are measured in pounds. I also drop the elasticity of transformation term to simplify disaggregation of individual outputs using a beta regression, which I discuss in Section 4.3.

I assume fishers produce desirable outputs using the following constant elasticity of substitution (CES) production technology:

$$f(\boldsymbol{x_{i,t}}) = \alpha\left(\sum_{j=1}^{k} \beta_k {x_{i,t,j}}^{\rho}\right)^{1/\rho} \tag{6}$$

where α is the factor productivity, β_k is the input share parameter where k is the number of production inputs, and ρ is the elasticity of input substitution. The sum of the β_k's is constrained to equal 1, and serves to scale inputs measured in different units (days and number of sets). To guarantee this condition is met I use the following parameterization developed by Gelman et al. (1996) for fractional parameters that sum to 1:

$$\beta_j = \frac{\exp(\phi_j)}{\sum_{m=1}^{k} \exp(\phi_m)}, \text{for } j = 1, \dots, k. \tag{7}$$

This specification allows each input share parameter to be defined by ϕ_j, which can take a proper normal prior.

I define vessel-specific technical inefficiency as μ_i, which I assume is exponential with a prior of 84%, based on earlier efficiency results from Sharma et al. (1998). I assume these inefficiencies are constant over time, which is a reasonable assumption given the 10-year period of observations. This implies that any year to year variation in a vessel's production, beyond that explained by input decisions, is captured as a normal stochastic shock.

2.4.2 Poisson Model for Undesirable Outputs

Sea turtle interactions for each species $s \in \{\text{loggerhead}, \text{leatherback}\}$ are observed each year t at the industry-level. I model the annual number of sea turtle interactions, $b_{s,t}$, as a truncated Poisson distribution, where d_t is the upper truncation point defined by the observed turtle interaction limit in year t. The model can be written as

$$\Pr(b_{st} | \nu, x_{i,t,shallow\ sets}, b_{st} \le d_t) = \frac{\frac{\lambda^k e^{-\lambda}}{k!}}{e^{-\lambda} \sum_{i=0}^{d_t} \frac{\lambda^i}{i!}}, \tag{8}$$

where the numerator is the PMF of the Poisson distribution and the denominator is the CDF at the truncation point d_t. Modeling sea turtle interactions in this way guarantees a policy invariant parameter estimate of ν. I parameterize the $\text{Poisson}_{\text{trunc}}$ model in terms of rate and exposure (Gelman et al. 2013). Although more commonly used in epidemiological studies, when applied to production of undesirable outputs, I interpret the rate parameter, ν, as industry-level environmental inefficiency. I model exposure using only shallow sets, $x_{i,t,shallow\ sets}$ because they generate nearly all observed sea turtle interaction events. I assume environmental inefficiency is constant over time, and identical for loggerhead and leatherback sea turtle interactions. This assumption implies the two sea turtle populations are identical and independent. In the current study, I lack sufficient data to separately identify the model for each sea turtle species, however, regulations are defined for the two populations separately, so I proceed assuming two identical and independent sea turtle populations.

2.4.3 Zero-Inflated Beta Regression Models for Output Share

In order to accurately assign market prices to predictions of aggregate output, $\theta_{i,t}$, and calculate the benefits of fishery production in the Bayesian decision analysis, the model must disaggregate $\theta_{i,t}$ into individual outputs for bigeye tuna, swordfish, and other desirable species. I accomplish this by transforming observed outputs into two parameters representing the share of output that is bigeye tuna, and the share of output that is swordfish. I then model these using a zero-inflated beta regression (Ospina and Ferrari 2010). Below, I define the share of aggregate output that is bigeye tuna for each vessel i in year t as $z_{1,i,t}$, and the share of remaining output that is swordfish as $z_{2,i,t}$.

$$z_{1,i,t} = \frac{y_{BE,i,t}}{y_{BE,i,t} + y_{SF,i,t} + y_{Other,i,t}}, \tag{9}$$

$$z_{2,i,t} = \frac{y_{SF,i,t}}{y_{SF,i,t} + y_{Other,i,t}}. \tag{10}$$

Using a zero-inflated beta regression has several advantages. I can model the relationship between output shares and the share of inputs that are shallow sets, which I define as $m_{i,t} = x_{i,t,shallow\ sets}/(x_{i,t,shallow\ sets} + x_{i,t,deep\ sets})$ for each vessel i in year t. By setting up the model in this way, I estimate an aggregate relationship between fishers' decisions of what to target and what they end up catching. Because fishing is inherently stochastic, this model accounts for uncertainty in catch composition. The zero-inflated beta regression employs a mixed beta-Bernoulli distribution to model shares that can equal 0, despite 0 being outside the support of the beta distribution. As applied to z_1 and z_2, the two models can be written as

$$\Pr\left(z_{1,i,t} \middle| \omega_1, \zeta_{1,i,t}, \xi_1\right) = \begin{cases} \text{Bernoulli}(\omega_1), & \text{if } z_{1,i,t} = 0 \\ \text{beta}\left(\zeta_{1,i,t}\xi_1, \left(1 - \zeta_{1,i,t}\right)\xi_1\right), & \text{otherwise} \end{cases}, \tag{11}$$

$$\Pr\left(z_{2,i,t} \middle| \omega_2, \zeta_{2,i,t}, \xi_2\right) = \begin{cases} \text{Bernoulli}(\omega_2), & \text{if } z_{2,i,t} = 0 \\ \text{beta}\left(\zeta_{2,i,t}\xi_2, \left(1 - \zeta_{2,i,t}\right)\xi_2\right), & \text{otherwise} \end{cases}, \tag{12}$$

where ω_1 and ω_2 represent the probability of that $z_{1,i,t}$ and $z_{2,i,t}$ are 0 respectively. The beta distributions are parameterized in terms of observed means $\zeta_{1,i,t}$ and $\zeta_{2,i,t}$ for each vessel each year, which are modeled as a function of the input share and average correlation parameter, and variances ξ_1 and ξ_2. Each mean is defined as

$$\zeta_{1,i,t} = \frac{\exp(o_1 m_{i,t})}{1 + \exp(o_1 m_{i,t})}, \quad 13$$

$$\zeta_{2,i,t} = \frac{\exp(o_2 m_{i,t})}{1 + \exp(o_2 m_{i,t})}, \quad 14$$

which is the inverse logit of $o_1 m_{i,t}$ and $o_2 m_{i,t}$, where o_1 and o_2 define the average relationship between $m_{i,t}$ and $z_{1,i,t}$ and $z_{2,i,t}$ respectively.

2.4.4 Estimation Results

Table 1 shows parameter estimates from the model fit to vessel-level data on annual inputs and outputs from 2004 to 2013, and industry-level data on observed sea turtle interactions from 2004 to 2013. I fit the model using Bayesian techniques implemented in Stan (Carpenter et al. 2017). Approximate convergence ($\hat{R} < 1.1$, Gelman et al. 2013) is achieved running four parallel Hamiltonian Monte Carlo chains for 1000 iterations each, discarding the first 500 samples in each chain. Posterior estimates are therefore calculated using 2000 samples from the posterior distribution. Figure 1 displays the sampling progression for nine of the model parameters. Sampling chains mix, and achieve convergence before the first 250 iterations, well before the end of the warmup.

The common production technology for desirable outputs is defined by the parameter estimates α, β_1, β_2, and ρ. The productivity scalar, α, translates input decision levels to output quantities which explains the large estimate. The input share estimate for shallow sets, β_2, is almost twice as large as the estimate for deep sets, β_1. This result is expected given trips dominated by shallow sets typically land more pounds of fish. The input elasticity of substitution, ρ, is estimated to be slightly greater than 1, which suggests deep sets and shallow sets are very slight complements, and fishers have a slight preference to mix inputs. The random standard deviation, σ_θ, is estimated in log scale, and therefore, quite large. This indicates substantial unexplained variation in desirable catch levels, which is expected given fishery production is driven by many factors beyond the control of fishers, including sea surface weather, fish movement, and oceanographic factors. Undesirable outputs are predicted using the environmental efficiency parameter, which I estimate to be very small, in line with the prior beliefs that sea turtle interactions are rare events.

For both beta regression models the probability of the share being 0 is low, ω_1 and ω_2, indicating that vessels are likely to catch at least some bigeye tuna or swordfish each year. For those vessels that catch at least some bigeye tuna or swordfish, coefficients from the beta regressions indicate that the proportion of annual inputs that are deep sets is positively related with the proportion of aggregate output that is bigeye tuna, o_1, and strongly negatively related to the proportion of the remaining output that is swordfish, o_2. These results suggest that deploying more deep sets are likely to catch mostly bigeye tuna and other desirable fish, while those deploying mostly shallow sets are likely to catch a mix of swordfish, bigeye tuna, and other desirable fish. The estimate of variance is larger for the beta regression predicting the share of remaining catch that is swordfish suggesting large unexplained variation in the share of swordfish and share of other desirable fish.

Figure 2 shows estimates of each vessel's technical efficiency. Vessels are ranked from most efficient to least efficient. This technical efficiency parameter is critical for modeling production at the vessel level because it accounts for heterogeneity in the production process between firms. Results indicate a fairly continuous distribution of vessels from the most technical efficient, close to 100%, to approximately 60%, with few gaps or clusters. Vessels below 60% technical efficiency decrease at a faster rate, with the lowest vessels operating below 50% technical efficiency.

2.4.5 Model Checking

I assess the fit of the model to the data using a series of posterior predictive checks. These checks compare simulated posterior predictions to observed data. I focus the posterior predictive checks to those quantities that directly enter the expected utility optimization: annual bigeye tuna, swordfish and other desirable species catch, and total annual Loggerhead and Leatherback sea turtle interactions. Figure 3 presents posterior predictions in green, and observed data in grey by year and output type. Posterior predictions for the three desirable species groups are summarized as annual expected catch for each vessel. For bigeye tuna and other desirable species there is substantial overlap between the distribution of predicted and observed annual vessel catch. For all years, the model tends to overpredict swordfish catch for vessels that catch very little swordfish, and underpredict swordfish catch for vessels that catch extremely large amounts of swordfish. This result is due to the large estimated variance parameter ξ_2, in the beta regression predicting the proportion of swordfish in the remaining aggregated catch. The misalignment between predictions and observations would be a greater concern if vessel level catch was used in the expected utility calculation to generate the main result of this paper, however, once aggregated the over and underpredictions compensate for each other. Posterior predictive checks of loggerhead and leatherback interactions are at the industry-level therefore posterior predictions are illustrated using all 2000 posterior draws. Because the model assumes identical interactions rates for loggerhead and leatherback sea turtles, posterior predictions are created from the same generative model. Each year, only one interaction level is observed for the entire industry, illustrated with a vertical grey line. In 2004, the industry deployed very few shallow sets as a result of reopening the fishery after a prolonged closure, therefore predicted interactions and observed interactions are both very small. For the remaining years, posterior predictions approximate observed interaction levels. Observations that lie in the extreme tails of the predicted interactions are balanced with 4 observed on the extreme right tail, and 3 observed on the extreme left tail. On the whole, the model fits the observed aggregate outputs fairly well.

2.5 Bayesian Decision Analysis

In this section I detail the steps for evaluating the decision analysis component of the model. The following outline summarizes the procedure.

1. Define the realistic set of decision outcomes.
2. Calculate the expected level of desirable and undesirable outputs for each element in the decision set using posterior predictions.
3. Define a sufficiently wide range of possible sea turtle values.
4. Finally, iterate over the range of defined sea turtle values and maximize the expected utility each iteration by finding the optimal decision level.

Fishery managers decide on the annual limit of loggerhead and leatherback sea turtles. I denote a particular decision d, and the set of all possible decisions D. Given observed decision levels, I constrain D to the set $\{1, 2, 3, \ldots, 50\}$. The set is restricted to feasible decision levels which reduces the time to evaluate a full Bayesian decision analysis.

The next step is to estimate the expected fishery outputs conditional on d. I accomplish this using the following procedure. I first draw the annual number of shallow sets for each vessel i, $x_{i,shallow\ sets}^{rep}$, from a truncated normal distribution with mean and standard deviation equal to the observed mean and standard deviation for that vessel. I then draw an annual number of sea turtle interactions, b^{rep}, from Eq 8, using posterior parameter estimates for ν. If $b^{rep} \leq d$, the sample of $x_{i,shallow\ sets}^{rep}$ are passed through to the next step. If $b^{rep} > d$, then new samples of $x_{i,shallow\ sets}^{rep}$ are drawn, multiplying the mean of each truncated normal distribution by $51/52$, representing a reduction in season length by 1 week. As long as $b^{rep} > d$, the mean of each truncated normal distribution is multiplied by further 1-week reductions in season length, returning to $51/52$ after $1/52$ is reached. Cycling through season length serves two purposes. It speeds up sampling for very restrictive levels of d, and it captures the impact of those decision levels on fishing season length. I approximate the $\mathrm{E}(b^{rep}|d)$ by taking the mean over all 2000 posterior parameter draws.

Once the condition is met that $b^{rep} \leq d$, the sample of $x_{i,shallow\ sets}^{rep}$ is used to estimate the desirable fish catch for each vessel. Because sea turtle interaction limits only apply to the shallow set sector of the fishery, I assume the number of deep sets is unchanged by the decision level. Therefore, for each vessel i, the annual number of deep sets $x_{i,deep\ sets}^{rep}$, is set to the observed mean for that vessel over the entire sample period. Again, using posterior parameter estimates, I draw an aggregated desirable output level θ_i using Eq 4. Separate output levels for bigeye tuna, $y_{i,BE}^{rep}$, are estimated by multiplying θ_i by the predicted output share parameter $z_{\mathbf{1},\boldsymbol{i}}$ and $z_{\mathbf{2},\boldsymbol{i}}$ drawn from Eq 11 and Eq 12 using annual input levels from the previous procedure. Similarly, $y_{i,SF}^{rep}$ is estimated by multiplying $\theta_i - y_{i,BE}^{rep}$ by $z_{\mathbf{2},\boldsymbol{i}}$, with the remainder attributed to $y_{i,Other}^{rep}$. I then approximate $\mathrm{E}\left(y_{BE}^{rep}|d\right)$, $\mathrm{E}\left(y_{SF}^{rep}|d\right)$, and $\mathrm{E}\left(y_{Other}^{rep}|d\right)$ by aggregating individual vessel catch and taking the mean over all 2000 posterior parameter draws.

Finally, I use the quantities $\mathrm{E}(y^{rep}|d)$ and $\mathrm{E}(b^{rep}|d)$ to optimize the following expected utility problem.

$$\max_{d}\left(p_{BE}\mathrm{E}\left(y_{BE}^{rep}|d\right) + p_{SF}\mathrm{E}\left(y_{SF}^{rep}|d\right) + p_{Other}\mathrm{E}\left(y_{Other}^{rep}|d\right)\right) - p_b\,\mathrm{E}(b^{rep}|d) \qquad 15$$

The price of desirable outputs is calculated as the mean observed market price over the sample period, adjusted for inflation. These calculations correspond to $p_{BE} = \$3.95$, $p_{SF} = \$3.14$, and $p_{Other} = \$2.12$. The value of sea turtles, p_b, is not observed, therefore the optimization problem is solved iteratively by substituting in values for p_b from the set $\{\$1000, \$2000, \$3000, \dots, \$30{,}000{,}000\}$.

The optimum is analytically solved by setting the first order condition of Eq 15 equal to 0. Rearranging the first order condition gives

$$p_{BE} \frac{\partial}{\partial d} \mathrm{E}\left(y_{BE}^{rep} \middle| d\right) + p_{SF} \frac{\partial}{\partial d} \mathrm{E}\left(y_{SF}^{rep} \middle| d\right) + p_{Other} \frac{\partial}{\partial d} \mathrm{E}\left(y_{Other}^{rep} \middle| d\right) = \ p_b \frac{\partial}{\partial d} \mathrm{E}(b^{rep} | d). \qquad 16$$

This defines the decision level at which the marginal benefits from fishery production (left-hand side) equal the marginal costs from sea turtle bycatch (right-hand side). The optimal decision level will vary depending on the value of sea turtles assumed. Plotting the range of sea turtle values and the corresponding optimal regulatory level visualizes the social demand for sea turtle regulation.

4.5.1 Decision Analysis Results

Figure 4 displays the optimal decision level over the set of simulated sea turtle values, and corresponding expected number of sea turtle interactions and expected total desirable catch. These expected quantities incorporate the effects of parameter uncertainty from model estimates, and uncertainty in the underlying data generating process through standard deviation in the desirable outputs model, and the shape of the Poisson distribution of sea turtle interactions. Panel A in Figure 4 displays the optimal decision level over the set of simulated sea turtle values. Panel B and C show the expected turtle interactions and desirable output levels that went in to the expected utility maximization. Reducing the decision level below 15 sea turtles per year increases likelihood the policy will be binding, thereby reducing the expected number of sea turtle interactions, and the expected desirable fish catch, reflecting the impact of shallow set fishery closure. This accounts for the trade-off modeled in the expected utility maximization.

The decision levels implemented from 2004 to 2009 implied a social value of loggerheads in the range of \$4.58 million-\$4.60 million, and leatherbacks in the range of \$4.60 million-\$4.63 million. As decision levels are relaxed, the implied social value of sea turtles asymptotes just below \$5 million. More restrictive decision levels quickly increase the implied social value of sea turtles. For instance, setting the annual sea turtle interaction limit to 5 is only optimal if the social value of sea turtles lies between about approximately \$9 million and \$12 million. Setting the decision level to 1 per year is only optimal above \$26 million.

2.6 Discussion

My results illustrate the use of Bayesian decision analysis to create a guide for regulators who must balance desirable fish production and damaging sea turtle bycatch. The framework I develop uncovers the implicit value of fishery damages to sea turtles that would make each decision level optimal. This information is critically important as it helps regulators assess the social values implied by their decisions. It does not, however, prescribe an optimal decision level. Rather, it serves as a common framework to facilitate stakeholder debate and build consensus around the social value of fishery damages. Once consensus is reached, regulators can use the model to map that value to the optimal decision level.

The approach is sufficiently general to serve regulators in other industries that jointly produce desirable and undesirable outputs. Regulators need only re-specify two key features: 1) a statistical model for production of desirable and undesirable outputs, and 2) an expected utility maximization of net social benefits resulting from production. The statistical model of production should capture the important input decisions made by firms in the industry, as well as describe how firm's desirable production contributes to the joint undesirable production of damages. The expected utility function must account for relevant quantities that make up the social benefits and costs of industry production, with expectations estimated for those quantities where uncertainty is important.

Under the specification assumptions used to model Hawaii's longline fishery, the results indicate observed sea turtle regulations imply large social values for damages caused by sea turtle bycatch. Under the regulations in place from 2004 to 2009 annual interactions limits were set to 16 for leatherback sea turtles and 17 for loggerhead sea turtles. Under these regulations, the expected desirable fish catch is estimated at 13.74 million pounds and 13.75 million pounds respectively, and the expected number of sea turtle interactions estimated as 9.72 and 9.78 respectively. Assuming these regulations optimized social net benefit, they implied social values for sea turtle bycatch of $5.1 million per leatherback, and $4.9 million per loggerhead caught. Further tightening these regulations would imply larger values. For instance, setting the annual sea turtle interaction limit to 5, implies a social value of sea turtle bycatch in the range of $8.9-10.6 million. At sufficiently high social values for sea turtles, greater than $30 million per sea turtle, the optimal regulation approaches fishery closure.

Moving in the other direction, more relaxed regulations imply lower social values for sea turtle bycatch. In 2012, sea turtle interaction limits were relaxed to allow for 24 leatherbacks and 34 loggerheads, the decision level moved toward asymptotic convergence. For limits greater than 20, the expected number of sea turtle interactions, and the expected desirable catch does not change very much. This reflects that the small probability of these regulations binding. For instance, the probability of fishery closure under the limit of 24 leatherbacks is 0.00001. Moving down the asymptotic tail, smaller sea turtle values very quickly relax the optimal decision level. If regulations confer some fixed cost to society, regardless of the likelihood they bind, this would suggest it becomes optimal to remove regulations below the asymptotic convergence value of approximately $5 million.

Any specific policy recommendations are conditional on knowing, or accurately estimating, the social value of sea turtle bycatch. Even without this information, the framework can still guide regulators in evaluating their decisions. For instance, results suggest that the current levels of sea turtle interaction limits are unlikely to bind. Therefore, regulators should consider abandoning bycatch regulations if they determine the values implied by their current decision reflect social norms. Similarly, tightening regulations beyond the 2004-2009 levels would not be optimal except under very large social values for sea turtle bycatch. In this way, the model can guide regulators through decision space, and indicate the region that is likely to achieve optimal net social benefits.

However, decision makers may be bound by constraints beyond the model's assumption that they maximize net social benefit. Regulations of sea turtle interactions are in fact legislated by the Endangered Species Act, which requires a biological opinion before an annual sea turtle interaction limit is adopted. Explicitly, the regulations are in place to ensure the long-term protection of endangered species. The published rational for a given decision level is therefore tied to the biological opinion, and not directly linked to any effects on net social benefit. That said, this model provides information on cases when there is misalignment between the two objectives. Or, there may be possible refinements that achieve greater net social benefits within the constraint that they protect species' viability.

The discussion above, of course, is contingent on having an accurate model of fishery production in Hawaii. Initial evaluations using posterior predictive checks (Figure 2) suggest that the model achieves a reasonably good fit to available data. Ultimate evaluation of the model should be based on whether or not the predicted quantities seem reasonable. But model results are also derived from a crucial set of assumptions. First, I assume fishers won't respond to policy levels in a way that changers the production technology. This could affect the results in two ways: When regulations are tightened fishers have strong incentives to improve their environmental efficiency. When regulations are relaxed, the opposite may occur, and fishers may adopt more damaging production practices. I also assume that technical efficiency estimates for individual firms are fixed through time. Finally, I assume a constant average price for the three fish types. In reality, these may be subject to exogenous shocks, or endogenous supply decisions.

2.6.1 Conclusion

In this paper, I have shown how Bayesian decision analysis can be used to evaluate regulatory trade-offs by uncovering the implicit value of damages generated by production. This analysis provides regulators with an optimal decision guide given information on the social value of damages. Although regulators might be well positioned to approximate this value through discussion with stakeholders, future empirical work could incorporate existing non-market valuation data to rigorously estimate the social value of damages. Combining these results would further expand the information set available to regulators, and increase the likelihood that regulations maximize net social benefits.

3. ANALYZING TUNA FISHER LABOR SUPPLY DECISIONS BY DECOMPOSING WAGE

3.1 Introduction

One of the fundamental pursuits of labor economics is to understand how people decide to allocate their time. Because time is a finite resource, factors that affect the amount of time people work, will also impact the amount of time remaining for other activities. In particular, labor economists have focused their attention on understanding how wage affects the amount of time people work. This is known as the labor supply decision.

Two competing theoretical models have been proposed to describe labor supply decisions. Under the neoclassical model, laborers maximize utility by allocating time to leisure and labor activities. When laborers experience positive transitory wage shocks, the substitution effect dominates the income effect, and the model predicts laborers will increase their utility by substituting leisure for labor, thereby increasing labor supply. Alternatively, under the target revenue model, laborers work until they achieve an existing income target. With positive transitory wage shocks, laborers are able to achieve their income target more quickly, and therefore reduce their labor supply. The applicability of these competing theories hinges on whether laborers increase or decrease their labor supply in response to transitory wage shocks.

To empirically evaluate these predictions, studies have sought labor contexts with frequent transitory wage shocks, and autonomous labor supply decisions. The results of these studies, however, have been mixed. Early studies of New York City and Singapore taxi cab drivers found large negative wage elasticities of labor supply, supporting a revenue target model (Camerer et al. 1997, Chou 2002). Similar results in support of the target revenue model were also found in scallop and tuna fisheries (Gautam et al. 1996, Nguyen and Leung 2013). Follow up work, however, on New York City taxi cab drivers noted a negative estimation bias with earlier measures of hourly wage. Once corrected, cab drivers appeared to follow neoclassical stopping behavior rather than targeting revenue (Farber 2005, 2008). Other studies of stadium vendors (Oettinger 1999), bike messengers (Fehr and Goette 2007), and lobster fishers (Stafford 2015) found substantial positive wage elasticities of labor supply, supporting the neoclassical model.

Much of the previous literature on labor supply assumes laborers respond directly to shocks in hourly or daily wage. As noted earlier by Farber (2005), hourly or daily wage, however, may not be the most salient factor to which laborers adjust the amount of time they work. In interviews with taxi cab drivers, he found fatigue was more often stated as the reason cab drivers stopped working.

In this article, I follow a similar line of inquiry as Farber (2005) and investigate whether laborers adjust the amount of time they work in response, not to daily wage, but to shocks to the components of wage. In particular, I decompose daily wage into a price and quantity component. The quantity component represents the part of a laborers' wage generated by the amount of service they sell, while the price component represents the price they receive for their service. One challenge with this line of inquiry is that in many contexts the price component is fixed, and hourly or daily quantities are rarely observed.[7] Hawaii's longline tuna fishery, however, provides an ideal context to investigate laborers response to the individual components of daily wage. Not only do tuna fishers make autonomous labor supply decisions, deciding how long to stay at sea each trip, but they are also subject to price shocks in the market, as well as quantity shocks while fishing, both of which are observed.

Using data from Hawaii's longline tuna fishery, I first model trip length conditional on daily revenue, following previous studies. I then decompose daily revenue into its components and model trip length using a Poisson regression. In addition to generating insight into the labor supply response to price and quantity shocks, the Poisson model also addresses statistical issues resulting from modeling a strictly positive count process with a log-linear normal regression. Because elasticities are not directly estimated in the nonlinear Poisson model, I compute them using posterior predictions to compare estimated elasticities of labor supply.

The result from the log-linear model with wage measured as daily revenue is similar to previous findings suggesting laborers more closely follow a target revenue model, with an estimated wage elasticity of labor supply of -0.05. After decomposing wage, I find that laborers respond differently to shocks to the price and quantity components of their daily revenue stream. With respect to price shocks alone, I estimate a slight positive price elasticity of labor supply, indicating laborers follow neoclassical predictions and work more when the price component of their wage increases. Interestingly, laborers respond in the opposite way to quantity shocks. I estimate a larger and negative quantity elasticity of labor supply, suggesting laborers work less when their wages increase as a result of higher quantities. Taken together these results indicate the response of laborers to wage shocks depends on the source of the shock. As the labor supply literature continues to develop, this appears to be an interesting direction of inquiry that may help resolve the conflicting predictions of the neoclassical and target revenue theories of labor supply.

To provide context for these results, I describe the fishery and the key labor decisions in Section 2. In Section 3 I document the data sources, and the decisions I make to prepare the data for model fitting. I present the models and results in Sections 4 and 5 and discuss the relevance of my findings in Section 6.

3.2 Background on Hawai`i's Longline Fishery

[7] For instance, taxi cab drivers have a fixed price per mile they drive, and stadium vendors sell merchandise for a set price.

Hawaii's longline fishery is the largest commercial fishery in Hawaii, operating in the Western and Central Pacific Ocean (WCPO) and Eastern Pacific Ocean (EPO). The fishery primarily targets bigeye tuna (*Thunnus obesus*) and swordfish (*Xiphias gladius*) generating an average annual revenue of $67.7 million, and landing on average 19.8 million pounds of fish annually between 2004 and 2013. Over this period, bigeye tuna has become the dominant sector of the fishery associated with 66% of total revenue and 51% of total landings.

Fish are caught using longline fishing technology, which consists of strings of baited hooks attached to a primary longline extending up to 100 km. Fishers choose between targeting tuna or swordfish by floating baited hooks at different depths. Swordfish are targeted by setting gear between 70 and 100 feet below the surface, while tuna are targeted much deeper, between 200 and 1200 feet below the surface. In addition to set depth, set location also varies depending on the target. Swordfish trips tend to fish farther north and east in the Pacific. As a result, the average trip length for trips targeting swordfish is 31 days, compared with trips targeting tuna that average 21 days. Because tuna dominates the fishery and operates distinct gear settings in separate locations, I focus on the commercial tuna sector for this study.

Entry into the fishery is limited by the availability of permits. A total of 164 permits are issued by NOAA to vessels for commercial longline fishing. Permits are freely transferable between vessels, so over time, the total number of vessels operating may exceed 164. In addition to holding a valid permit, tuna fishers are required to fill out logbook forms, and are regulated by annual catch limits for bigeye tuna set each year in the WCPO and EPO. Between 2004 and 2013 the tuna fishery was forced to closed twice, in 2009 and 2010, after reaching the annual catch limit of 3,763 mt in the WCPO (Pan 2014).

Vessels vary in length, hold size, and storage technology, but are typically operated by a captain and around 3 crew. Once at sea, captains decide where to fish and how many days to stay out. Although there are no restrictions on how long vessels stay at sea, most vessels land before they hit their maximum capacity. Upon returning, vessels land their catch at the Honolulu fish auction, where fish are auctioned individually to a set of wholesalers who participate in a competitive bidding process. Prices vary from fish to fish and are a function of quality, supply, and demand. A vessel's daily revenue is therefore determined by how much they catch each day fishing, and the prices they receive once they land.

3.3 Data

Vessel captains are required to fill out logbook forms for every fishing trip they operate. On these forms they record the vessel name, permit number, commercial license, target species, departure date, return date, the date, time and location of each set they deploy, including the total number of hooks, and catch from each set. Once vessels land their catch at the Honolulu Fish Auction, the auction records the species, price per pound, and total number of pounds for each fish sold, as well as the vessel name, and commercial license of the landing vessel.

I join observations from the Hawaii longline logbook data, and Honolulu Fish Auction Dealer data for trips operated between 2004 and 2013. Because vessel names are more likely subject to variation in spelling, I join observations using commercial license and return/landing date. Once the two data sources are joined, I generate a unique trip number from the permit number and departure date to uniquely identify all fishing trips. I then classify trips targeting tuna as those that only deployed deep sets, defined by the number of hooks attached to the floating devices on the longline. All other trips deploying at least one shallow set I classify as swordfish trips, and discard from the data. For each tuna trip, I then aggregate the total number of hooks deployed on each trip, the total pounds of bigeye tuna landed, and the total value of all fish landed. I also measure the average bigeye tuna price on the day that each trip landed initially landed their catch.

Before generating the variables used for model fitting, it is important to consider the impact of measurement error on parameter estimates. Both Camerer et al (1997) and Farber (2005) noted the negative bias in the wage parameter estimates resulting from measurement error in hours worked. Because hours worked is both the outcome variable and used to calculated hourly wage by dividing daily wage by hours worked, even mean 0 measurement error in hours worked will negatively bias the parameter estimate by created erroneously low hours worked with erroneously high daily wage observations, or vice versa. In this case, the magnitude of the bias is related to the magnitude of measurement error. More generally, when the measurement error under consideration only impacts input variables, the effect is often assumed to result in attenuation bias. This is true only under strong assumptions and need not be the case more generally. Factors including model structure, the joint distribution between measurement error and all other input variables in the model, and the possibility that measurement error is correlated with true values can affect whether measurement error results in attenuation bias, exaggeration of the effect, or sign reversal (Bound et al. 2001). Indeed, even when strong assumptions of "classical" measurement error are met, small sample sizes (N < 4000) can lead to exaggerated estimates of effect size (Loken and Gelman 2017). Common fixes used to correct for measurement error bias, such as instrumental variable methods, are only valid when the strong assumptions of "classical" measurement error are met, and the model is linear. In many empirical cases, these do not hold, and the correction procedures can actually make matters worse. When possible, data validation is a very useful technique for empirical researchers to quantify measurement error, and reduce the bias associated with it, and does not require a strong set of assumptions (Bound et al. 2001).

With this in mind, I construct a set of model input and outcome variables. Because the return date for each trip is recorded in both the logbook form and the Honolulu Fish Auction data, I am able to validate the return date for all trips. I exclude trips where the landing date recoded by the Honolulu Fish Auction is more 1 day later than the logbook return date. My decision to include trips where there is a 1-day discrepancy is based on wanting to reduce measurement error in trip length while also allowing for realistic flexibility in landing behavior.[8] For those trips that meet this criterion, I calculate a trip length variable for each trip by counting the number of days between the departure date and return date. I then calculate daily trip wage by dividing the total trip revenue recorded at the auction by trip length. Although the above validation procedure does not account for error in departure date, it is the best available method to remove negative bias in the parameter for daily trip wage associated with measurement error in trip length given data resources. I then calculate two additional input variables representing the decomposition of daily wage in to a price and quantity component. To measure the price component, I calculate the average price of bigeye tuna observed at the Honolulu Fish Auction over the days of the trip. The quantity component is a measure of the daily productivity of fishing, in other words whether the fishing was good or bad. Therefore, I measure this by calculating the average catch rate for each trip as the total pounds of bigeye tuna caught divided by the number of hooks. Although this calculation represents an association between two variables, it does not yield negative bias in parameter estimates noted by Camerer et al. (1997) and Farber (2005) because the divisor does not appear as the outcome variable in the model. Because of the large sample of trips, any "classical" measurement error in these two variables will only lead to attenuation bias. To give a sense of the data, Figure 1 displays the time trend for the primary variables used in this study: trip length, average daily bigeye tuna price, and the log of trip catch rate. Finally, I standardize the units of both the average price of bigeye on the landing date and trip catch rate by subtracting the mean and dividing by two standard deviations (Gelman 2008). This input standardization procedure allows for the comparison of effect size for inputs measured in different units, and between indicator parameters on the 0-1 scale.

3.4 Models

To investigate how laborers respond to the decomposed components of daily wage I preform analysis on a set of two models. The first model is a reproduction of empirical labor supply models used in previous literature. The log of labor supply is modeled as a linear function of the log of wage, the coefficient of which is interpreted as the wage elasticity of labor supply. This, however, estimates the sample average wage elasticity of labor supply, which may mask several interesting insights. If laborers in fact respond to price signals, or information indicating particularly productive periods of work, then the previous model will only estimate the aggregate effect. Such an aggregation may explain the ambiguous results

[8] I have heard through personal communication that some trips choose, or are asked to land their catch the day after they return.

from previous studies evaluating neoclassical model predictions. The second model investigates this possibility by modeling labor supply as a Poisson processes, where the mean is determined by the price and quantity components of wage. In addition to accounting for the strictly positive count nature of labor supply outcomes, the estimated model parameters indicate the separate relationship between each wage component and labor supply.

3.4.1 Log Linear Model with Wage

For each trip t, operated by vessel i in month m, and year b, I model the log of trip length, $\log y_{timb}$, as a normal distribution with standard deviation, σ_y. The mean is specified as a function of the log of average daily revenue, $\log w_{timb}$, with indicator parameters for individual vessels α_{i-1}, months η_{m-1}, and years δ_{b-1}, and an intercept term μ.

$$\log y_{timb} \sim \mathrm{N}\left(\mu + \beta \log w_{timb} + \alpha_{i-1} + \eta_{m-1} + \delta_{b-1}, {\sigma_y}^2\right)$$

By including a set of vessel, month, and year indicators, the model accounts for vessel-specific idiosyncrasies, monthly seasonality, and annual trends. The parameter of most interest is β, which is interpreted as the wage elasticity of labor supply. The estimate of β is comparable with previous estimates from earlier studies in the labor supply literature.

3.4.2 Poisson Model with Decomposed Wage

To consider the separate effects of the price and quantity components of wage, I model trip length, y_{timb}, using a Poisson regression. The model is kept as similar as possible to previous normal linear model to make model comparison easy. Within the Poisson regression framework the mean is given by an exponentiated term. In this model I include in this term the standardized average tuna price on the initial landing date of each trip, p_{timb}, to represent the price component of wage, and the standardized average catch rate for the trip, r_{timb}, to represent the quantity component, the same set of vessel, month, and year indicators as above, and intercept μ.

$$y_{timb} \sim \mathrm{Poisson}\left(e^{\mu + \beta_1 p_{timb} + \beta_2 r_{timb} + \alpha_{i-1} + \eta_{m-1} + \delta_{b-1}}\right)$$

The two primary parameters of interest are β_1 and β_2 representing the relationships between the price and quantity components and trip length. Comparing these two parameters provides insight into the separate effects of the price and quantity components of wage on labor supply decisions. The exponential of each coefficient is interpreted as the percent by which trip length changes from a 1 unit change in input. The model does not, however, directly generate estimates of the elasticities of labor supply, therefore, these are calculated using posterior simulations.

3.4.3 Model Estimation

I estimate both models using Bayesian inference fitting each to the full set of prepared data, consisting of 9,854 trip observations from 203 unique vessels over the period 2004 to 2013. Computations were performed using Stan (Stan Development Team 2017), which implements a Hamiltonian Monte Carlo (HMC) sampling algorithm. Samples were obtained by running four parallel chains of 1000 iterations each, throwing away the first 500 as warm-up samples. Posterior estimates are therefore computed using 2000 samples from the posterior distribution. I monitored approximate sampling convergence using the criterion of $\hat{R} < 1.1$ (Gelman et al. 2013).

3.5 Results

3.5.1 Log Linear Analysis with Wage

Table 1 shows posterior estimates from the analysis of the log linear model with wage measured as average daily revenue for each trip. The primary parameter of interest, β, is interpretated as the average wage elasticity of labor supply. The median estimate, -0.04, corresponds to a 4% decrease in trip length if average daily revenue were to double. This reduction in trip length represents the average comparison between trips that differ in average daily wage, but are identical in vessel characteristics, month of year, and year. The estimate of the random error term, σ_y, is large considering the dependent variable is measured on the logarithmic scale, indicating substantial variation in trip length not explained by average daily revenue, or the set of indicators included in the model.

3.5.2 Poisson Regression with Decomposed Wage

Fitting the Poisson regression model described above examines the individual relationships between the price and quantity components of wage and the labor supply decision measured by trip length.

Figure 2 compares the parameter estimates for β_1 and β_2, corresponding to the standardized price and quantity components of average daily wage. The first observed difference in the two parameters is their sign. The price component of daily wage has a positive relationship to trip length, while the quantity component is negatively related. This indicates that trips that observer higher tuna prices are longer on average than those observing lower prices, while trips with high catch rates are shorter on average than those with low catch rates. Because the two variables were standardized by subtracting the mean and dividing by two standard deviations, the relative effect sizes of each can also be directly compared from the figure. Based on the median posterior estimates, the effect size of the quantity component is more than twice as big as that estimated for the price component of wage, indicating that differences in catch rates correspond to larger differences in trip length than differences in average tuna price during the trip.

To provide a better economic interpretation of parameter estimates for the standardized price and quantity components, I calculate a set of elasticities of labor supply corresponding to price and quantity components measured at trip lengths along the distributional range. Figure 3 shows five points along the range of trip lengths measured from posterior simulations of the baseline data, doubling catch rates, and doubling average tuna price. At the five points shown, doubling catch rates is predicted to shorten the shortest and the longest trips, while doubling prices is only seen to predict an increase in the medium-long trips.

These posterior simulations can be converted into traditional elasticity estimates using the two equations below.

$$\frac{dy_p/y_p}{dp/p} = \frac{\%\Delta y_p}{100\%}$$

$$\frac{dy_r/y_r}{dr/r} = \frac{\%\Delta y_r}{100\%}$$

The predicted percent change in trip length resulting from the simulated change in price and quantity components is given by $\%\Delta y_p$ and $\%\Delta y_r$ respectively. Computations are made easier by simulating a doubling of both the price and quantity components making the denominator 1. The calculated elasticities of labor supply for the five points in Figure 3 are shown in Table 2. One of the features of calculating elasticities from posterior simulations is that elasticities can be measured at individual percentiles rather than as a sample average. Average elasticities of labor supply can also be calculated over the entire set of 2000 posterior draws by approximating the expected trip length for each scenario as the mean of draws. These calculations result in estimates of average price elasticity of labor supply of 0.03, and catch rate elasticity of labor supply of -0.01.

Figure 4 displays the posterior estimates for the set of indicators included in model. Estimates of the indicators for month of year, η, show that September has the longest trips on average, and January the shortest, with a clear seasonal cycle. Average trip length is also estimated to be increasing over the years as seen in the year indicator estimates, δ. Since 2009, however, average trip length has been relatively constant. Finally, the vessel-specific indicators, α, show large differences in average trip length between vessels. This indicates a large amount of trip length variation owes to vessel-specific idiosyncrasies.

The standardization procedure used to scale the price and quantity components of wage also allows direct comparison between those estimates and the effect sizes of parameter estimates for indicator variables measured as 0 or 1. Comparing the largest and smallest estimates from each set of indicators provides a sense of the relative effect sizes for months, years, and vessels. Months and years have about the same effect size measuring the median estimates for the largest and smallest indicators. Vessel-specific indicators have an effect size nearly four times larger. All of these are much larger than the two continuous variables measuring the price and quantity components of wage.

3.6 Discussion and Conclusions

Over the period for which I have data, trip records indicate that the relationship between wage and labor supply can be decomposed into two separate components with opposite relationships to labor supply decisions. Fishers on average take longer trips when the average fish price is high but take shorter trips when the average catch rate is high. By comparing the effect size of the two estimates, the negative effect of higher catch rates is more than twice the positive effect of higher prices. Both components contribute to the average daily wage for each trip, suggesting distinct responses of laborers to two different information signals composing daily wage, with catch rates providing the dominant signal.

Comparing the estimates of the decomposed wage components to the log-linear estimate using an aggregate measure of daily wage, it appears that daily wage masks an important positive relationship between prices and labor supply decisions. Although the estimate using daily wage presented here is substantially smaller than that estimated by Nguyen and Leung (2013), it is consistent in sign, suggesting the wage elasticity of labor supply for tuna fishers is indeed negative. However, the results from the decomposed wage model indicate the negative sign may be driven by an underlying relationship between catch rates and trip length. Separating this quantity component from the price component of daily wage reveals a previously hidden positive relationship between price and trip length.

There may be several reasons why the relationship between the components of wage differ from one another and from the aggregate measure of wage as average daily revenue. The first possible reason is that they may measure different things. Each variable is an approximation of the underlying model factor and is limited by an understanding of the fishery and the availability of data. It must be assumed that daily trip revenue, and its components are an accurate reflection of the relevant factors entering fishers labor supply decisions in order for an interpretation corresponding to these factors to be accurate. If this assumption is not valid, the measured variables may be representing unrelated and spurious relationships. However, if the assumption holds and the variables measure the factors with which they are assumed to correspond, the second possible reason for the difference in estimates is that fishers in fact interpret the two types of information separately. Fishers may interpret a surge in price as indication that their fishing effort is more valuable and respond by extending trips, while interpret high catch rates as an opportunity to achieve an existing revenue target in a shorter amount of time, thereby reducing trip lengths.

This interpretation points to a potentially interesting theoretical insight. Laborer may be inconsistent in their responses to the different components making up wage and span theoretical frameworks. When exposed to price information, laborers may respond following neoclassical predictions, but respond following revenue targeting behavior when exposed to quantity information. This suggests further research exploring the conditions under which laborers make decisions, and the characteristics of different wage information streams may lead to improved understanding of labor incentives and laborers responses through labor supply decisions.

This research is relevant to many industries. Uber, for example, relies on surge pricing to manipulate drivers labor supply decisions and increase taxi service in areas and times of high demand. Recent research suggests this strategy is effective (Chen and Sheldon 2015). Results from this paper indicate the success of surge pricing may owe to signaling laborers through the price component of wage, rather than affecting their aggregate wage directly. The quantity component, which in the taxi industry can be measured by the efficiency by which drivers link fares together, provides an alternative signaling path with the potential to generate an even larger labor supply response.

Similarly, this research may be relevant to fishery management where the problem of overfishing can be interpreted as the result of excess labor supply. Implementing policies that can reduce labor supply to that corresponding with sustainable fishing levels would provide fishery managers with a new set of tools to achieve sustainable fishing. For instance, periods of high fish price or growing demand can be identified as particularly vulnerable to excess labor supply and allow managers to initiate policies such as taxing landings. With respect to the quantity component of wage, investing in technologies that increase catch rates, may indeed lead to more efficient fishing, and an overall reduction in labor supply.

A. TABLES FOR CHAPTER 1

A1. Data summary of annual input costs in dollars for WCPO, EPO, and SF targets from the Cost and Earnings Survey in 2012.

Inputs	Mean WCPO (SD)	Mean EPO (SD)	Mean SF (SD)
Fuel	$154,045 (62,542)	$27,134 (31,917)	$16,318 (44,331)
Captain Pay	$75,700 (47,061)	$13,623 (18,167)	$6,962 (19,937)
Crew Pay	$47,255 (46,103)	$7,245 (12,246)	$1,978 (6,192)
Bait	$48,722 (17,761)	$7,928 (8,635)	$4,013 (10,787)
Other	$31,477 (12,796)	$5,029 (5,652)	$3,195 (8,844)
Hooks	$19,346 (8,583)	$3,160 (3,479)	$2,062 (5,618)

A2. Time series data summary of total active and modeled vessels from the 2005 to 2013 dealer data. Because some vessels fish more than one target, total vessels modeled can be less than the sum of each target.

Year	Total Vessels Operating[1]	Total Vessels Modeled	Vessels modeled (WCPO)	Vessels modeled (EPO)	Vessels modeled (SF)
2005	125	105	103	41	11
2006	127	112	111	11	10
2007	129	116	115	53	13
2008	129	118	115	79	11
2009	127	120	118	73	15
2010	124	119	115	86	15
2011	129	124	122	83	16
2012	129	128	127	94	17
2013	135	126	124	83	10

[1]Data from https://pifsc-www.irc.noaa.gov/library/pubs/DR-14-016.pdf.

A3. Summary of calibrated parameters for vessels modeled vessel and target-specific PMP model. The mean and standard deviation for each target-specific parameter are given.

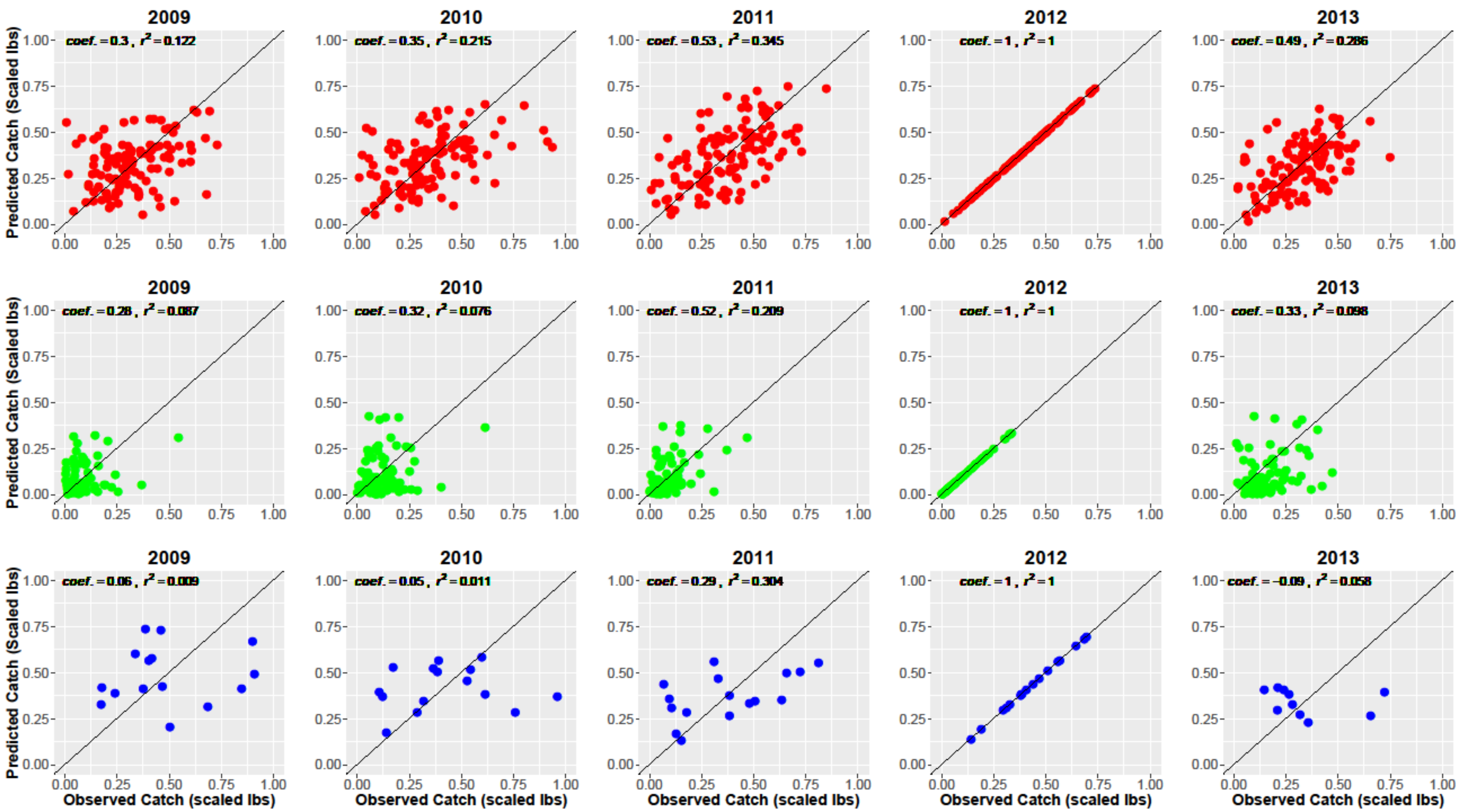
Description	**Symbol**	**WCPO**	**EPO**	**SF**
Scale parameter	α	1,104.02 (418.80)	382.38 (305.60)	1,629.79 (496.58)
Shadow value	λ	-7.70 (NA)	-7.57 (NA)	-4.45 (NA)
Unobserved price of catch	μ	17.42 (4.65)	24.00 (16.33)	10.41 (2.32)
Share parameter for fuel	β_{fuel}	0.42 (0.10)	0.57 (0.24)	0.89 (0.16)
Share parameter for captain pay	β_{cap}	0.19 (0.08)	0.14 (0.10)	0.04 (0.07)
Share parameter for crew pay	β_{crew}	0.12 (0.09)	0.08 (0.08)	0.02 (0.02)
Share parameter for bait	β_{bait}	0.13 (0.03)	0.10 (0.06)	0.02 (0.04)
Share parameter for other	β_{other}	0.08 (0.03)	0.07 (0.04)	0.02 (0.03)
Share parameter for gear	β_{gear}	0.05 (0.02)	0.04 (0.02)	0.02 (0.02)

A4. Mean observed and the median difference between observed and predicted input expenditures. Observed data came from the 2005 Cost and Earnings Survey. All values are adjusted to 2012 dollars. The median difference and p-values are from a two-sample paired Wilcoxon test.

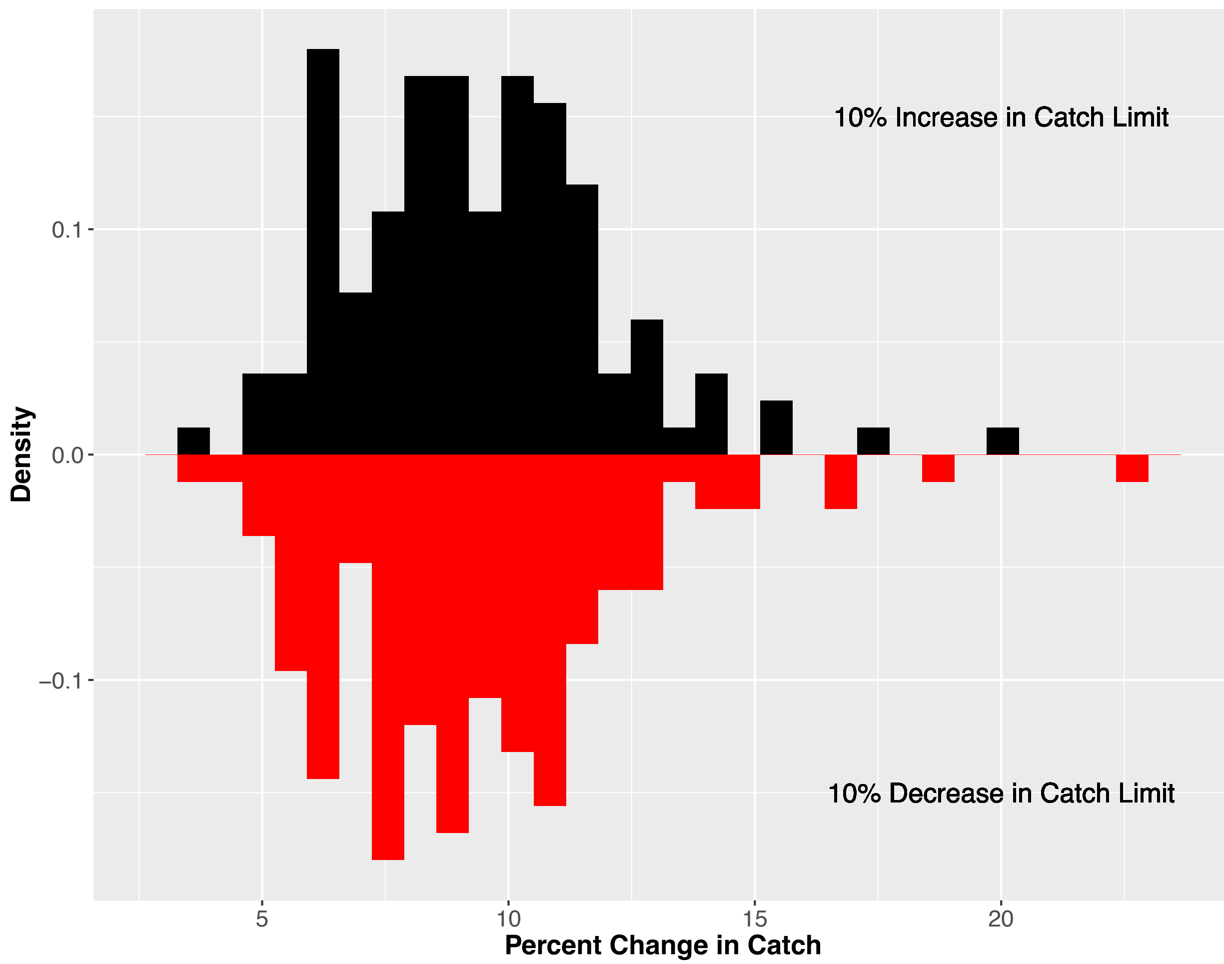
	WCPO		EPO		SF	
Inputs	**Mean Observed (dollars)**	**Median Predicted Difference (P-value)**	**Mean Observed (dollars)**	**Median Predicted Difference (P-value)**	**Mean Observed (dollars)**	**Median Predicted Difference (P-value)**
Fuel	106,532	-25,324 (<0.001)	10,972	9,388 (0.059)	22,349	-4,563 (NA)
Captain Pay	84,114	-19,017 (0.038)	7,404	5,789 (0.101)	11,937	4,229 (NA)
Crew Pay	56,204	-27,395 (<0.001)	5,150	3,523 (0.022)	9,744	6,471 (NA)
Bait	39,544	45 (0.984)	3,627	5,141 (0.007)	8,312	7,561 (NA)
Other	32,259	-5,599 (0.011)	2,635	2,920 (0.011)	4,785	10,807 (NA)
Gear	17,426	-1,136 (0.389)	1,430	2,153 (<0.001)	4,006	3,866 (NA)
Sample	71		25		1	

B. FIGURES FOR CHAPTER 1

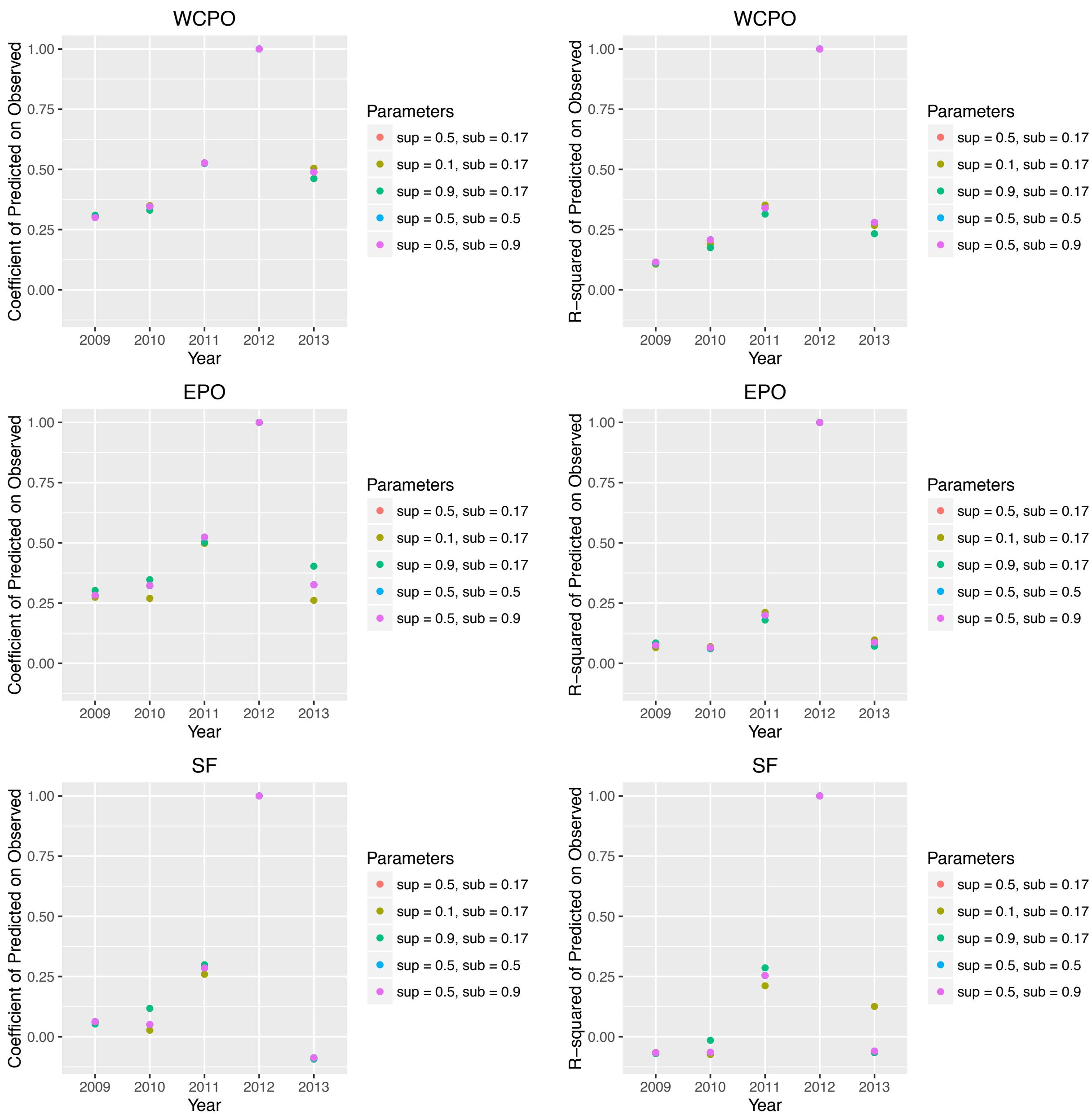
B1. Evaluation of model predictions of individual vessel catch for bigeye in the WCPO (red), bigeye in the EPO (green), and swordfish (blue) from 2009-2013. The solid line indicates the 45-degree line. The correlation coefficient and R-Squared from the linear model are given in the top-left corner of each plot. Axes are scaled so the maximum catch is 1 to prevent disclosure of confidential data.



B2. Distribution of responses for individual vessels measured by the percent change from 2012 catch levels. Results from 10% increase in annual catch constraint from 2012 are given filled black and represent increases in catch. Results from 10% decrease in annual catch constraint from 2012 are filled red and represent decreases in catch.



B3. Sensitivity analysis measuring the effect from changing assumed supply elasticity and substitution elasticity values on model prediction results from 2009-2013.



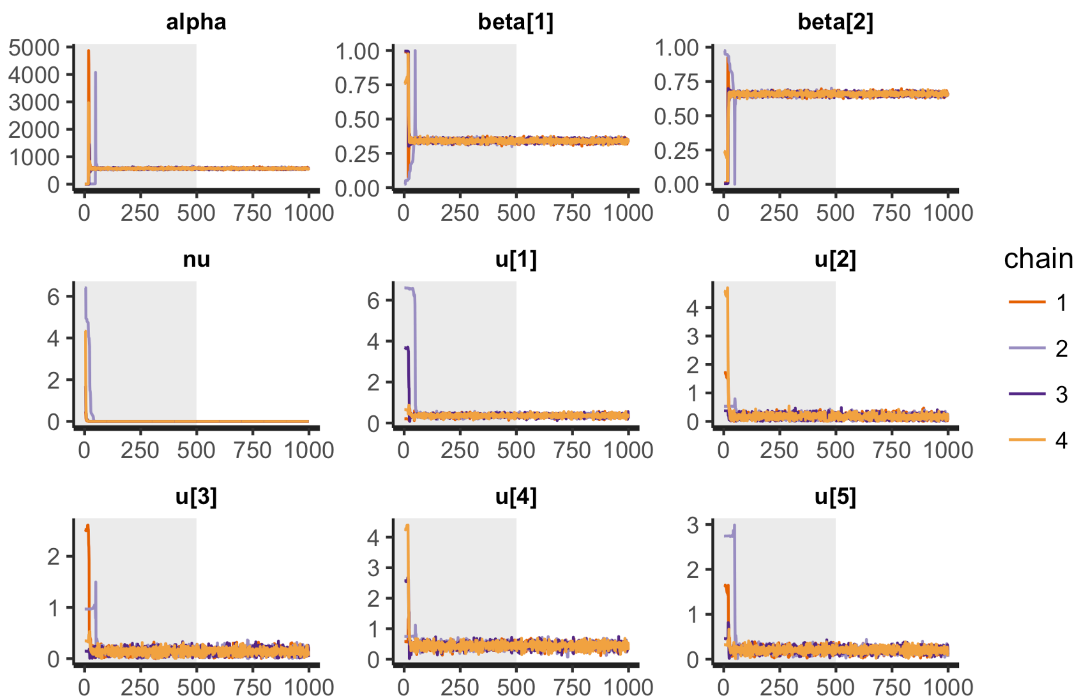
C. TABLES FOR CHAPTER 2

C1. Posterior estimates of the primary model parameters and calculated $\hat{R}$ measure of convergence.

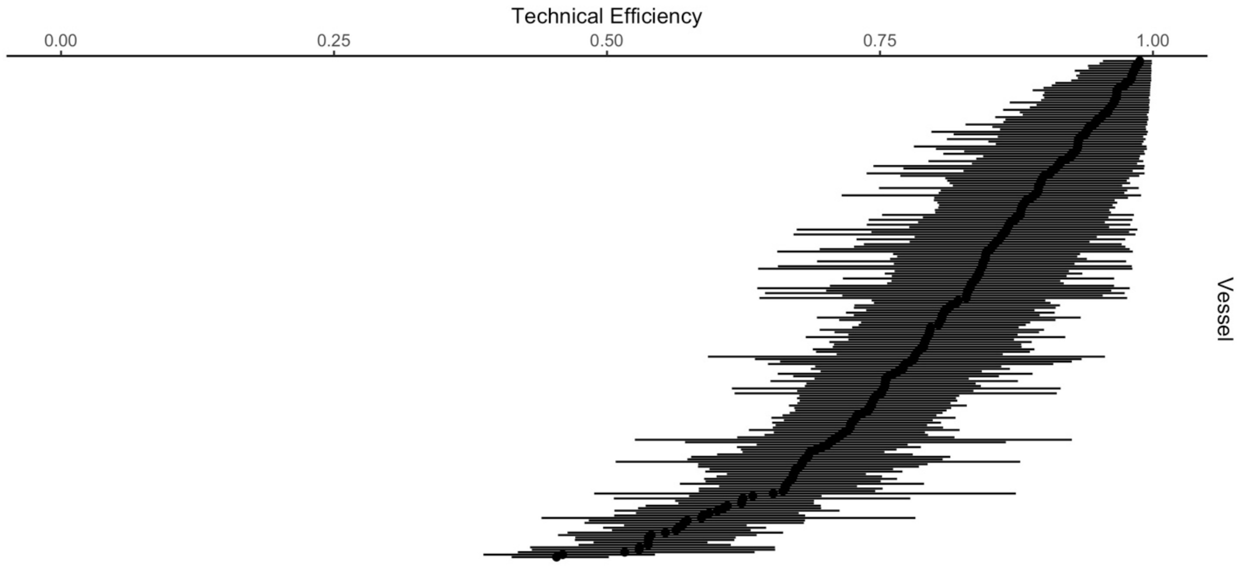
Parameter	Description	Mean	2.5%	97.5%	$\hat{R}$
α	Productivity scalar	568.26	529.47	608.78	1.01
β_1	Input share of deep sets	0.34	0.32	0.37	1.00
β_2	Input share of shallow sets	0.66	0.63	0.68	1.00
ρ	Input elasticity of substitution	1.10	1.00	1.21	1.00
σ_θ	Random error term for model of aggregated output	0.18	0.17	0.19	1.00
ν	Environmental efficiency	0.0015	0.0012	0.0017	1.00
o_1	Coefficient of beta regression for share of catch that is bigeye tuna	0.09	0.06	0.13	1.00
o_2	Coefficient of beta regression for share of remaining catch that is swordfish	-2.05	-2.12	-1.98	1.00
ξ_1	Variance of beta regression for share of catch that is bigeye tuna	0.47	0.01	1.33	1.00
ξ_2	Variance of beta regression for share of remaining catch that is swordfish	1.13	0.64	1.99	1.00
ω_1	Probability of the share of total catch that is bigeye tuna is 0	0.0007	0.0000	0.0026	1.00
ω_2	Probability of the share of remaining catch that is swordfish is 0	0.0173	0.0110	0.0250	1.00

D. FIGURES FOR CHAPTER 2

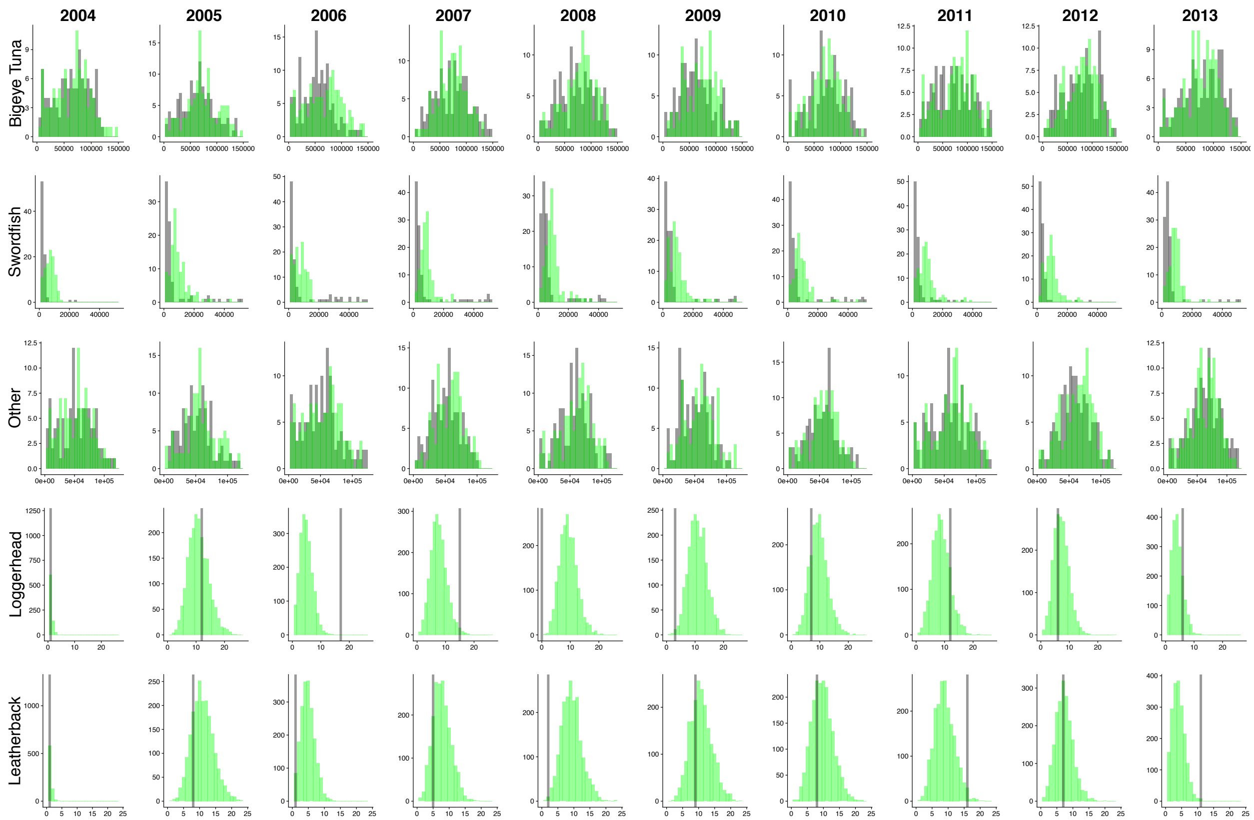
D1. Sampling process for the four chains displayed for 9 model parameters.



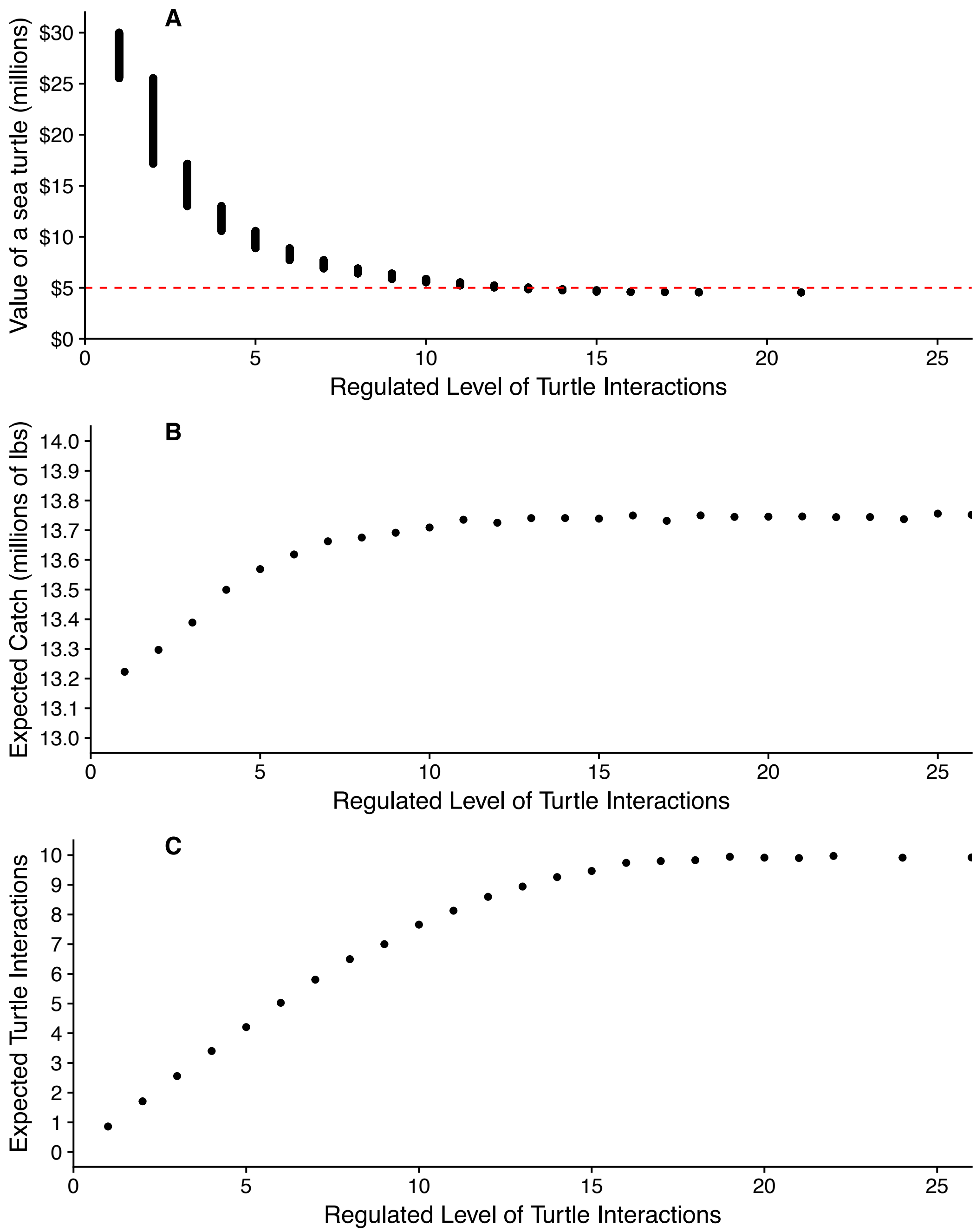
D2. Ranked estimates of vessel-specific technical efficiency with medians indicated by dots and 10%-90% ranged indicated with lines.



D3. Posterior predictive checks comparing observed (grey) and predicted (green) model outcomes.



D4. Summary of results from the decision analysis. Panel A displays the optimal regulation across the set of sea turtle values with red dashed line at $5 million for reference. Panel B shows the aggregate expected catch at each regulatory decision level, and Panel C shows the expected number of turtle interactions for either Loggerheads or Leatherbacks at each regulatory decision level.



E. TABLES FOR CHAPTER 3

E1. Posterior estimates of the wage elasticity of labor supply, β, and standard deviation of error term, σ_y, for the log-linear model with aggregate measure of wage as average daily trip revenue.

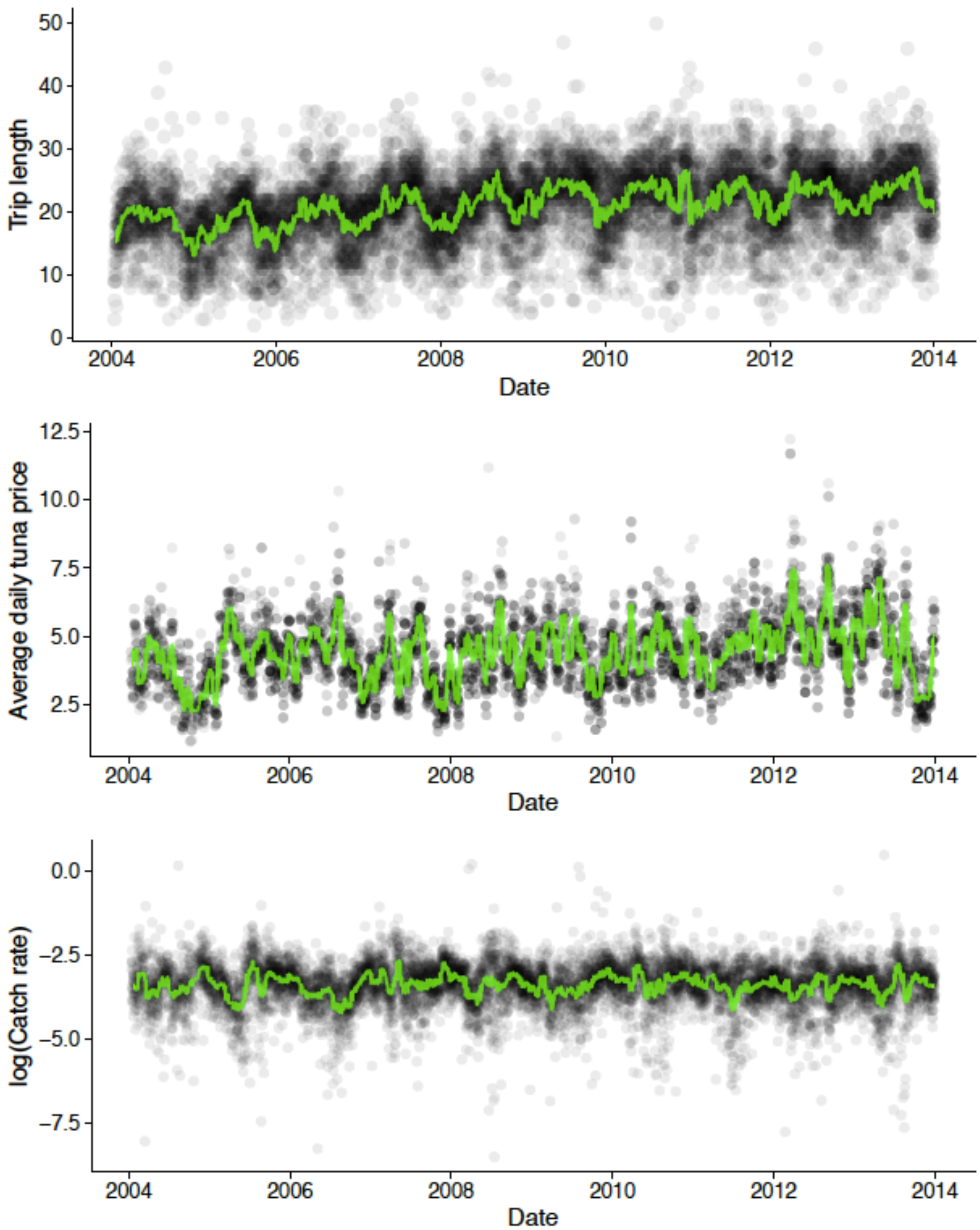
Parameter	2.5%	50%	97.5%	$\hat{R}$
β	-0.05	-0.04	-0.03	1.0
σ_y	0.25	0.25	0.25	1.0

E2. Calculated price elasticities of labor supply and catch rate elasticities of labor supply for the five percentiles shown in Figure 3.

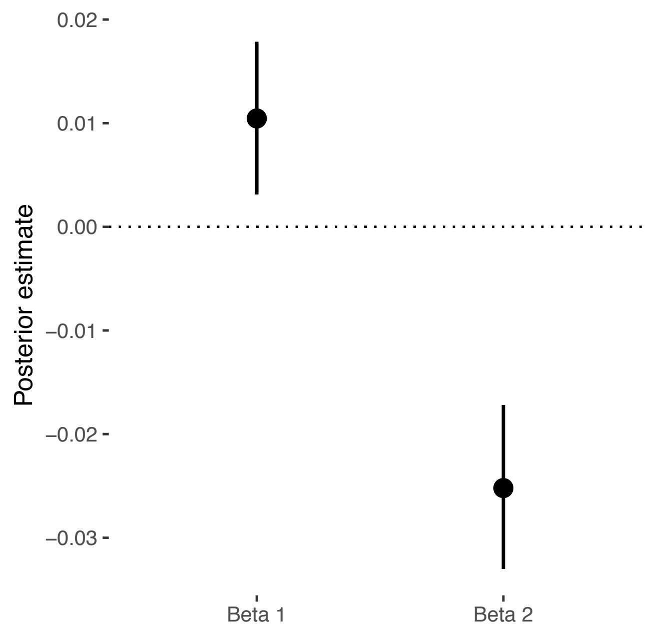
	10-percentile	20-percentile	50-percentile	80-percentile	90-percentile
$\frac{dy/y}{dp/p}$	0.00	0.00	0.00	0.04	0.00
$\frac{dy/y}{dr/r}$	-0.07	0.00	0.00	0.00	-0.03

F. FIGURES FOR CHAPTER 3

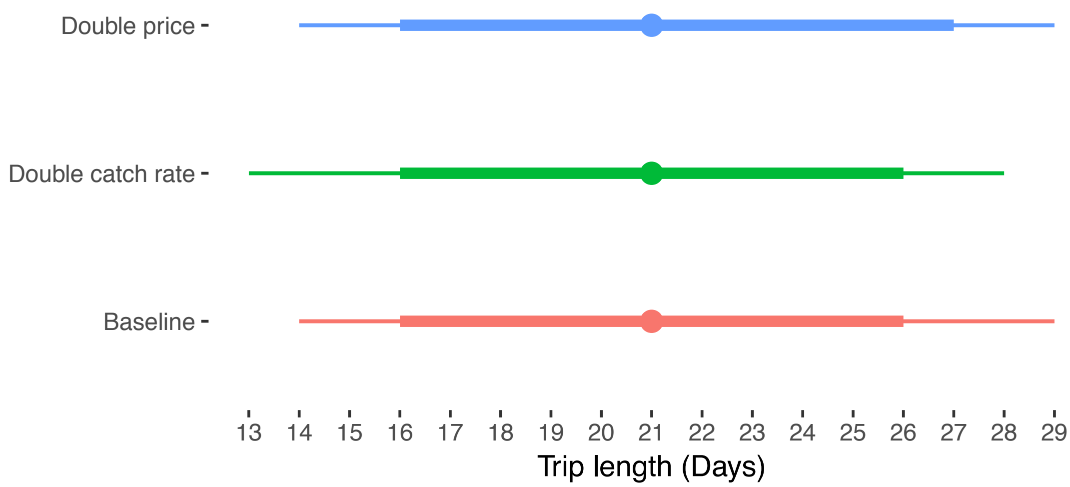
F1. Trip length, average daily tuna price, and the logarithm of catch rates for trips observed over the sample period from 2004 to 2013. Dots indicate trips or days in the case of average daily tuna price, and green line indicates the 40-day moving average.



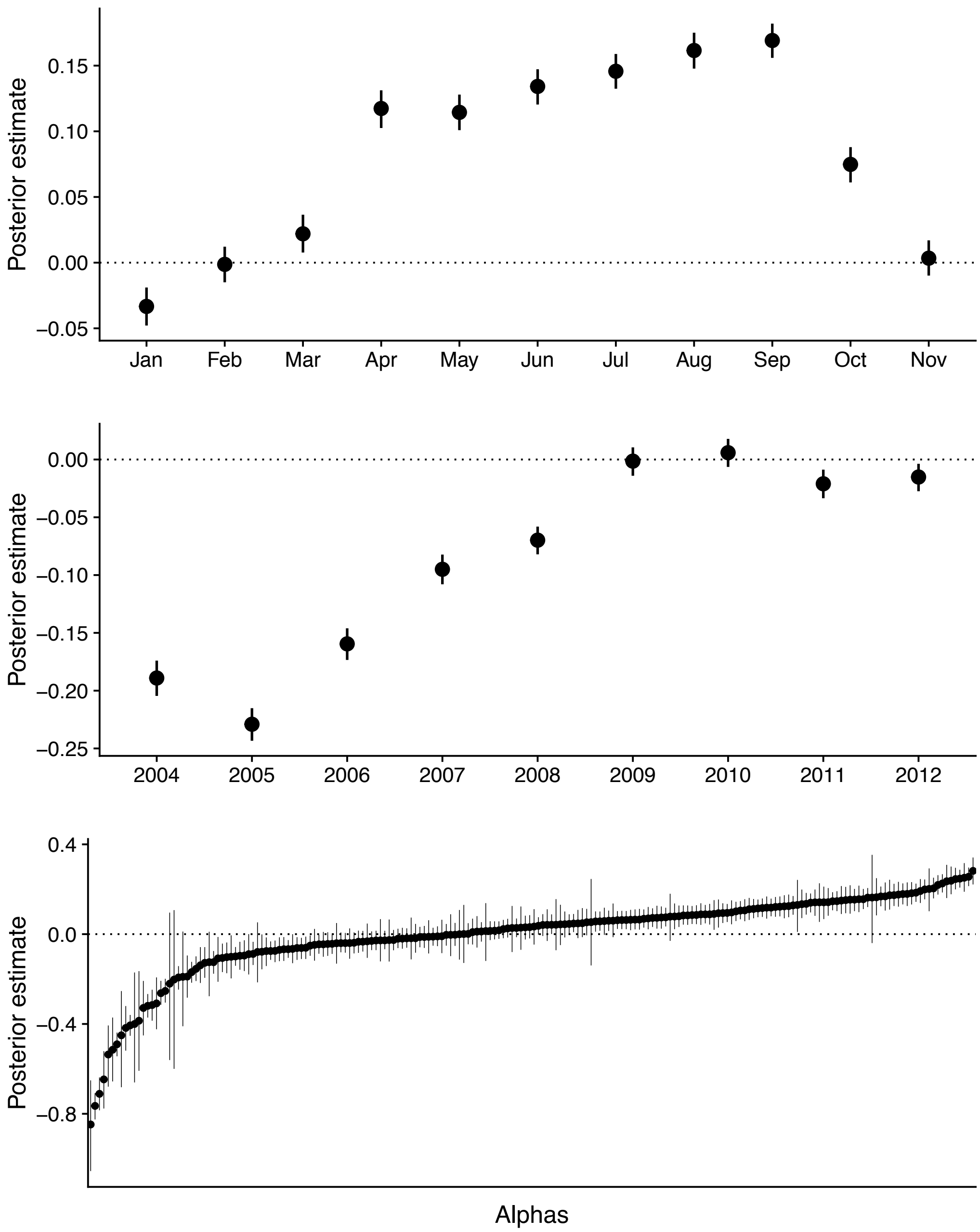
F2. Coefficients (and 10%-90% interval) of the price (Beta 1), and quantity (Beta2) components from the Poisson regression model.



F3. Posterior simulations of trip lengths for baseline data, data with doubled catch rates, and data with doubled price. Point indicates median predicted trip length, thick line indicates 20%-80% range, and thin line indicates 10%-90% range.



F4. Coefficients (and 10%-90% interval) for month indicators, year indicators, and vessel-specific indicators (Alphas) ranked in increasing order, modeled in the Poisson regression with price and quantity wage components.



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